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FACTORS DETERMINING WINE PRICES IN HUNGARY, ESPECIALLY REGARDING GEOGRAPHICAL INDICATIONS

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Factors determining wine prices in Hungary, especially regarding geographical indications

PhD dissertation

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1 INTRODUCTION

The purpose of this dissertation is to reveal the factors influencing wine prices in the Hungarian market. The focus of my study is on the factors that resolve the information asymmetry between the sellers and the buyers (consumers) of wines, and how these elements explain the differences in prices between individual wines.

The history of winemaking and consumption goes back thousands of years (Lőrincz and Barócsi, 2010), and this tradition is deeply embedded in Western culture. However, from a scientific point of view, wine is not only a popular topic for consumption or production. Wine critic Hugh Johnson excellently summarises this in the preface of his book titled The Story of Wine: *"Why is wine so special? First of all, because throughout its history — and thus the history of mankind — it has been a remedy and courage: wine was medicine, disinfectant, and the only means of refreshing a tired soul that helped to overcome all the misery of body and soul. At the same time, it has almost been the only luxury item for a thousand years, despite its unpredictable and ever-changing value - not just the product of two vineyards, but not even that of two vintages was of the same quality"* (Johnson, 2004 p.8).

According to Storchmann (2012), winemaking, wine and especially good wine – although Chaikind (2012) provides many other examples of theoretical history – , is first and foremost important for economists because of its large price differences, long ageing potential (during which it can also increase its value), the relationship between the price and vintage and the fact that its quality, being an experiential good, can only be assessed after it has been consumed.

In addition to scientific considerations, other personal and practical factors appear in the motivation of my research and even my application for the PhD program. On the one hand, as a senior government employee, wines are one of my (main) fields of expertise. Still, various issues of winemaking have already been the subject of my university papers and both of my bachelor and master theses. Another personal (probably the most private) motivation is to understand the processes in the sector better as a member of a wine-producer family.

In terms of its diversity, the world of wine stands out significantly from other sectors of agriculture. This variety also appears on the market, and it is not common that any agricultural product to be priced so differently by their producers or sellers.

The thesis examines several factors related to wine prices, with particular attention to geographical indications (GIs), as their collective nature raises many issues for further analysis. First, the relationship between wine and its origin, analysed by many for ages, is reflected by geographical indications (on the label). Secondly, differences in prices associated with geographical indications and the relationships as well as decisions of local producers are also interesting on a policy basis. This policy attention is made even more justified by the fact that, of the factors explaining wine prices in my dissertation, the real possibility of the regulation (on international, European Union, Member State or local community levels) arises only in the case of geographical indications.

Since the 1992 reform, quality has been an increasingly important feature of the European Union's Common Agricultural Policy (CAP), with the most important assumption being that the quality of agricultural products and foodstuffs is linked to their origin. That is why the CAP has introduced three quality terms: the protected designation of origin (PDO), the protected geographical indication (PGI), collectively referred to as geographical indications (or GIs for short), and the traditional specialities guaranteed (TSG). The regulation of geographical indications derived from the French wine law and became part of the European Union's wine market regulation during the 2006-2009 wine reform (Meloni and Swinnen, 2013).

The Hungarian wine sector is highly fragmented in many respects, and only the institution of geographical indications is suitable for shaping the diverse local conditions and traditions into market value. Accordingly, the issue of geographical indications (or, in other words, more commonly used in Hungary, the protection of origin) may be of interest from a social science point of view beyond wines. This can be referred to as a marketing tool created by collective action, the credibility of which arises from its land-locked characteristic, while it values from its non-reproducibility. This unrepeatable nature, as well as the legal system that protects it, can, *in theory*, provide a serious opportunity for producer communities to increase the profitability of their activities.

Thus, in the framework of the identification of the factors explaining the differences in wine prices, the dissertation gives special attention to the geographical indications and the factors influencing their role.

In the course of my research, I focus on the Hungarian wine market and the wines, in a narrower sense.

1.1 Structure of the dissertation

In this dissertation, after a brief description of the world wine market, including the Hungarian market, I analyse the literature on the factors influencing wine prices, followed by the presentation of my research.

In the first chapter, after describing the motivation and the goal, I first clarify the interpretation of the basic concepts used in the dissertation (wine, wine quality), then I present the world wine market in detail and analyse the most important trends and changes of the last 20-25 years. This is followed by a description of the specifics of the Hungarian wine sector, detailing the diversity of Hungarian wine regions, the GI system reflecting this, and their significance.

The second chapter provides a detailed description of the literature. I examine the factors affecting wine prices in 5 broad groups: the place of origin / geographical indications, expert ratings, objective quality factors (e.g. chemical composition), other traditional labelling elements (e.g. grape variety, vintage, individual brand) and other (not elsewhere classified) factors. A critical analysis of the literature follows this, the primary aim of which is to draw conclusions about my research from both theoretical and methodological points of view.

The third chapter presents my research and its methodology. I describe the research questions in detail, as well as a total of my 10 hypotheses. Next, I present the operationalisation of the research questions and the examination of hypotheses, the models to be applied, followed by the methods of data collection.

Chapter four contains a detailed presentation of the results, while conclusions are drawn in chapter five.

1.2 Definitions and oenological basics

I consider it necessary to clarify the meaning of the concepts used several times in this dissertation, even if they are considered evident because there is a lot of public belief about the world of wine, which can lead to many misunderstandings or inaccurate interpretations.

The first notion of being clarified is wine. According to the International Organization of Vine and Wine (OIV), “Wine is the beverage resulting exclusively from the partial or complete alcoholic fermentation of fresh grapes, whether crushed or not, or of grape must. Its actual alcohol content shall not be less than 8.5% vol. Nevertheless, taking into account climate, soil, vine variety, special qualitative factors or traditions specific to certain vineyards, the minimum total alcohol content may be able to be reduced to 7 %vol. by legislation particular to the region considered.” (OIV, 2019a, p.3).

However, the law of the European Union (and accordingly the Hungarian wine law) also knows a narrower notion of wine. In a broader sense, the word wine refers to all (17) wine products (e.g. wine, sparkling wine, quality sparkling wine, aerated sparkling wine, wine vinegar). The definition of wine in the narrower sense (Annex VII, Part II, point 1 of Regulation (EU) No 1308/2013) determines its minimum actual alcoholic strength, maximum total alcoholic strength and minimum acidity. In addition, EU law contains a list and detailed rules for authorised oenological practices (Annex VIII to Regulation (EU) No 1308/2013 and Annex I.A to Regulation (EU) No 2019/934).

In the thesis, I use the word “wine” in the narrower sense, I use the term “wine product” for the broader notion of wine. During the thesis, the wine quality is emphasised several times, so it is worth clarifying what we mean by it, as well as what factors influence it according to the oenological literature. I describe wine quality as a multidimensional phenomenon, one dimension of which is the quality level, and the other dimension is made up of elements that can be described as characters as a whole. These two dimensions of wine quality each raise a number of questions, and overall they are challenging to grasp.

The quality level can easily be characterised, for example, by scores determined by experts, but this does not affect the description of the character as two wines with very different characters (e.g. white and red) can get the same score. The wine character itself contains many aspects that can be grouped in several ways. One approach is to group the elements of a wine character according to which of our senses we experience them - based on this, we distinguish the description of the colour, aroma and taste of the wines. The other approach focuses on what elements are found in every wine and what are not. Accordingly, we distinguish between structure (acidity, alcohol content, sugar content, tannin content, finish, etc.) and ornamentation (decoration: aromas and flavours such as fruity, spicy, animal). In describing these elements, we characterise them primarily, but not exclusively, by marking their intensity and quality level (e.g., “much but mature tannins”).

Figure 1

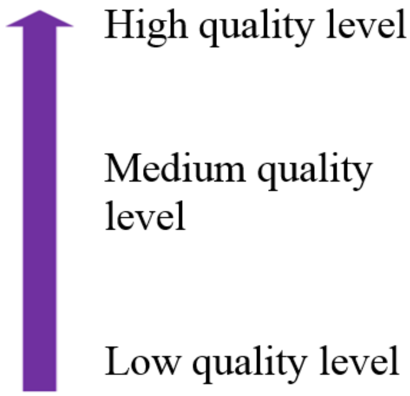
Visualisation of the dual dimensions of wine quality regarding character

clarity of appearance	intensity of appearance	colour shade	clarity of aroma	intensity of	acidity	alcohol content	sweetness	tannin content	body	flavour intensity	finish	fruity	spicy	vegetal	woody
structure												ornamentation			

Source: Own composition based on WSET (2014)

Figure 2

Visualisation of the dual dimensions of wine quality regarding quality level



Source: own composition

Different sensory ratings typically strive for objectivity and a systematic approach, and most of the experts involved aim to train themselves continuously. Still, at the same time, we must not forget that these surveys are always based on human perception.

Accordingly, expert ratings are typically considered a subjective element in the literature (Ling and Lockshin, 2003; Gál, 2006; Thrane, 2009).
The wine world uses several scales to display the quality level (Robinson, 2019), of which the 100-point system of the OIV (2009) stands out, which allows a very systematic, scientifically demanding analysis of the judged wines.
One of the most common (though perhaps less popular by the oenologist profession) methods for describing a character is the Systematic Approach to Tasting by the Wine and Spirits Education Trust (WSET, 2014). What these two methods have in common is that they approach the subject of the study by systematically going through the elements found in all wines, analysing and evaluating them from a common point of view. However, the end product of the analysis itself is fundamentally different, given the very different nature of the quality level and the character. The essence of the difference between these two dimensions is illustrated in Figures 1 and 2.

An alternative interpretation of wine quality is given by Botos and Szabó (2002), distinguishing between classification, technological and perceived quality. Instead, this grouping focuses on how wine quality is examined from different perspectives (regulation, production, consumption). According to them, wineries strive to ensure that the resources invested in classification and technological quality increase the quality perceived by the consumer.

A number of factors influence the quality of wine products (Eperjesi, 2010), and the effect of a factor considered to be of minor importance may be decisive in some cases. Following Gál (2006), these factors can be classified into four groups, which are illustrated in Figure 3.

The factors determining wine quality are presented here according to Gál (2008). The first factor is the place of origin, including its climatic, physiographic, edaphic and biotic characteristics: the climate, the topography, the soil and the populations of the species living in the area. Humans (i.e. the winemaker) have relatively little influence on the factors of origin beyond the choice of the location of the plantation. Therefore, this decision is of crucial importance.

The place of origin includes the climate of an area: perennial light, heat and precipitation conditions. These can be interpreted at different territorial levels (wine region, wine district, settlement, cru or even a plot). We can talk about varying levels of climate accordingly.

Physiographic conditions refer to topographic conditions (altitude of the plantation, exposure and angle of the slope) as well as latitude. Large bodies of water (rivers, lakes, sea) and forests close to the area are also included. All of these have an impact on the climatic factors of the place of origin.

Figure 3

Factors determining wine quality

Source: Gál (2006, p.4)

By edaphic conditions, we mean the soil of a given area. The soil also has an effect on the direct function of the vine, but its impact can even be felt directly in the taste of the wine.

By biotic conditions, we mean flora and fauna of the vineyard and its surroundings (e.g. *Botrytis cinerea* which may produce *aszú* berries).

The second factor is the vintage, by which we mean the weather of a given year. This is a factor that can be considered as delivered, we cannot change the weather consciously, according to our intentions, in accordance with our economic interests. However, mitigating the negative effects of a bad vintage is possible with certain technological interventions (e.g. limiting the yield of a plantation - Barócsi, 2006, and Gál, 2006).

The third factor is the grape variety. On the one hand, this can be seen as a matter of absolute human choice, because a plantation can be grafted or replanted at virtually any time. However, the quality of a particular variety can be strongly influenced by the place of origin. Some varieties produce high quality nowhere, others produce quality only in certain areas, while again others produce great quality almost everywhere (most of them are so-called international varieties).

The fourth factor is the human, that is, the viticulture and oenological technology applied, which by definition depends entirely on human decisions.

The weight of each factor is different for each specific wine, as is the possibility of their reproducibility. In theory, some grape varieties can be planted in any area suitable for viticulture (others only to a more limited extent), and the technology can be transferred, learned, copied. At the same time, the effect of human behaviour on vintage effects cannot be controlled, so the effects of weather itself cannot be reproduced. Although humans can choose the place of origin, it is not possible to transport it elsewhere, and it is expensive to re-create it, so this factor cannot be reproduced either. Therefore, origin plays a vital role in the development of differences between wines. The actual biological mechanism of action of these effects is described in detail by Crespy (2003) and van Leeuwen et al. (2004). It should be added that the influential role of origin may vary from one wine region to another. Königer et al. (2003) pointed out that in the southern wine regions, the effect of soil and in the northern wine regions, the effect of physiographic factors (e.g. the effect of topography on climate) is significant. It is important to note here that the *place of origin* and *terroir* are not synonymous concepts – the latter one, in addition to the place of origin in the narrower sense, includes the human factors (e.g. traditional knowledge and technology) (OIV, 2010).

This suggests that the place of origin is the key for the real, non-reproducible uniqueness of wines. Accordingly, in the long run, emphasising the place of origin (but even more the terroir) or enforcing its effects on wine quality may be a strategy that pays off for wineries.

1.3 The world wine market

Grapes are basically grown for three purposes in the world: making wine products, table grapes and dried grapes. Only certain areas of the Earth are suitable for economic wine grape production, typically between the 30th and 50th latitudes in the Northern hemisphere and between the 20th and 40th latitudes in the Southern hemisphere (Eperjesi, 2010). Traditional wine-growing regions are typically found in Europe, but especially in the second half of the 20th century, we witnessed a steady advance in non-European wine-producing countries. Accordingly, wine-producing countries today are usually divided into two groups. The Old Wine World (OWW) covers the traditional European countries, the vast majority of which are now members of the European Union. The three largest are France, Italy and Spain. The New Wine World (NWW) typically includes former British or Spanish colonies (United States, Chile, Argentina, South Africa, New Zealand, Australia, to a lesser extent Mexico, Brazil, Uruguay). Emerging wine producers like China and India are generally not part of the New Wine World.

Below, I present the development of world viticulture over the past two decades based on the OIV (2019b) database.

1.3.1 Production of wine products

The most important data on world wine production are summarised in Table 1. The production data collected by the OIV always refer to the volume of new wines produced (fermented) in a given year, so it would be more difficult to observe trends using annual data (due to their high volatility as vintage conditions may vary to a high extent). Therefore, I used five-year moving averages.

During the period under review, the annual world production fluctuated between 253.7 million (1995) and 297.8 million hectolitres (2004) but basically stagnated.

Table 1 shows the development of the New Wine World very well, the production of this group of countries increased by about 30% during the examined period.

The production of the Old Wine World, and thus its dominance, parallelly decreased significantly, by 8 percentage points, by about 10%. The three largest wine-producing countries are stable, accounting for about half of the world's wine production, although their share has fallen significantly, by five percentage points.

The European Union continues to dominate the production of both the world and the Old Wine World. Although the EU's dominance in the Old Wine World has increased, mainly as a result of multi-round enlargements (from 70% to 91%), its global decline is well illustrated by the fact that, despite enlargements, its share has fallen by 2 percentage points over the period.

Table 1

World wine product production (five-year moving average), 1000 hectolitres, 1997-2014

Period	World	EU	3 Big	OWW	NWW	EU (%)	OWW (%)	NWW (%)	3 Big (%)
1995-1999	267 250	163 849	140 855	194 489	59 488	61%	73%	22%	53%
1996-2000	272 298	167 955	144 830	197 940	60 354	62%	73%	22%	53%
1997-2001	270 780	164 967	142 210	194 019	61 920	61%	72%	23%	52%
1998-2002	268 977	163 083	139 940	190 987	62 688	61%	71%	23%	52%
1999-2003	269 412	161 620	138 333	190 253	63 607	60%	71%	24%	51%
2000-2004	272 782	161 139	138 253	191 214	65 683	60%	70%	24%	51%
2001-2005	272 535	158 785	135 848	188 127	68 116	59%	69%	25%	50%
2002-2006	275 993	160 512	137 595	189 464	69 869	59%	69%	25%	50%
2003-2007	278 132	160 899	137 945	190 359	70 923	60%	68%	26%	50%
2004-2008	279 111	160 144	137 055	189 517	72 610	60%	68%	26%	49%
2005-2009	273 424	155 288	132 932	183 936	72 398	60%	67%	26%	49%
2006-2010	270 419	152 376	130 822	181 212	72 039	60%	67%	27%	48%
2007-2011	267 357	148 809	127 714	177 769	72 241	60%	66%	27%	48%
2008-2012	265 748	146 464	125 758	174 117	73 471	59%	66%	28%	47%
2009-2013	270 111	149 212	128 945	176 254	75 359	59%	65%	28%	48%
2010-2014	270 234	149 200	129 062	174 748	76 691	58%	65%	28%	48%
2011-2015	272 750	150 863	130 346	176 003	77 707	59%	65%	28%	48%
2012-2016	273 051	152 460	132 123	176 331	77 577	59%	65%	28%	48%

Source: Own composition based on OIV (2019b).

The rise of the most recent wine-producing countries is indicated by the fact that while at the beginning of the period countries in neither group accounted for 5% of production, this value rose steadily to 7% by the end of the period.

1.3.2 Vineyard area

Unfortunately, the OIV statistics on the size of vineyards do not include a breakdown by the purpose of viticulture. Hence, Table 2 contains data for all vineyards, regardless of the actual use of the crop.

The area of vineyards was the largest at the beginning of the period and the smallest at the end, with a decrease of almost 5%. Here, too, the decline of the EU and the Old Wine World, as well as the advancement of the New Wine World, are well observable.

Despite of the enlargements, the vineyard area of the EU has decreased, especially in the 2008-2012 period as an impact of the grubbing-up scheme introduced by the 2006-2009 reform of the Common Market Organisation of wine.

Table 2

Size of vineyards in the world, hectares, 1995-2016

Year	World	EU	3 Big	OWW	NWW	EU (%)	OWW (%)	NWW (%)	3 Big (%)
1995	7 807 634	3 604 039	3 049 646	5 552 182	984 089	46%	71%	13%	39%
1996	7 703 329	3 548 636	2 997 941	5 440 544	1 005 218	46%	71%	13%	39%
1997	7 654 766	3 539 201	2 992 136	5 371 210	1 033 671	46%	70%	14%	39%
1998	7 629 364	3 527 109	2 984 036	5 313 579	1 074 807	46%	70%	14%	39%
1999	7 716 554	3 546 530	3 002 079	5 283 772	1 139 838	46%	68%	15%	39%
2000	7 773 738	3 514 765	2 983 891	5 230 617	1 193 166	45%	67%	15%	38%
2001	7 786 462	3 467 683	2 943 076	5 152 673	1 212 435	45%	66%	16%	38%
2002	7 809 168	3 435 005	2 911 750	5 103 104	1 242 775	44%	65%	16%	37%
2003	7 816 114	3 409 710	2 897 779	5 060 551	1 251 850	44%	65%	16%	37%
2004	7 771 318	3 547 669	2 878 916	4 997 909	1 261 831	46%	64%	16%	37%
2005	7 717 824	3 498 123	2 827 268	4 908 477	1 280 761	45%	64%	17%	37%
2006	7 681 805	3 469 744	2 812 085	4 856 191	1 295 835	45%	63%	17%	37%
2007	7 603 300	3 728 622	2 782 032	4 767 354	1 306 877	49%	63%	17%	37%
2008	7 541 021	3 665 519	2 733 948	4 704 325	1 317 666	49%	62%	17%	36%
2009	7 495 563	3 569 642	2 650 927	4 599 275	1 336 522	48%	61%	18%	35%
2010	7 481 840	3 484 140	2 579 505	4 491 521	1 339 704	47%	60%	18%	34%
2011	7 466 072	3 391 516	2 500 074	4 394 102	1 348 039	45%	59%	18%	33%
2012	7 480 959	3 355 641	2 474 741	4 318 153	1 349 923	45%	58%	18%	33%
2013	7 516 315	3 366 211	2 471 390	4 281 942	1 354 395	44%	57%	18%	33%
2014	7 553 974	3 342 055	2 453 353	4 258 599	1 356 191	44%	56%	18%	32%
2015	7 504 272	3 308 996	2 440 848	4 214 963	1 341 218	44%	56%	18%	33%
2016	7 463 909	3 313 110	2 453 835	4 197 808	1 332 180	44%	56%	18%	33%

Source: Own composition based on OIV (2019b).

1.3.3 Consumption

Table 3 shows data on wine consumption. It is important to point out that these data are typically calculated from the wine balance (taking into account production, stocks and foreign trade).

Over the period concerned, world consumption of wine products increased significantly, by almost 7%, while the structure of consumption changed severely.

While at the beginning of the period nearly two-thirds of consumption was accounted for traditional wine-producing countries of the Old Wine World, and the most important wine-producing countries together accounted for 88%, by 2016 this proportion had fallen to 51% and 77%, respectively. This change has been even greater between wine-producing and the non-wine-producing Member States of the European Union. While at the beginning of the period, traditional wine-producing countries consumed almost ten times as the non-producing Member States, by 2016 this difference had melted to just over four times (taking into account the 15 countries that were only members in 1995, the same proportion in 2016 was less than four).

Table 3

World consumption of wine products, 1000 hectolitres, 1995-2016

Year	World	EU prod.	Non-EU prod.	OWW	NWW	EU-prod. (%)	Non-EU prod. (%)	OWW (%)	NWW (%)
1995	227 425	117 127	12 140	150 654	50 860	52%	5%	66%	22%
1996	221 646	113 176	12 596	144 753	49 358	51%	6%	65%	22%
1997	225 137	110 145	14 544	142 862	50 184	49%	6%	63%	22%
1998	228 321	112 393	14 903	141 203	50 496	49%	7%	62%	22%
1999	225 747	111 581	16 230	138 010	51 397	49%	7%	61%	23%
2000	225 740	112 185	17 850	140 342	51 426	50%	8%	62%	23%
2001	227 642	110 942	19 168	140 776	51 297	49%	8%	62%	23%
2002	230 031	109 288	20 266	140 225	52 686	48%	9%	61%	23%
2003	237 947	110 594	21 245	144 046	54 859	46%	9%	61%	23%
2004	237 673	114 122	22 494	142 244	55 235	48%	9%	60%	23%
2005	238 749	113 249	23 590	140 223	57 075	47%	10%	59%	24%
2006	243 253	113 420	23 209	142 667	58 098	47%	10%	59%	24%
2007	250 241	118 784	24 876	144 754	60 176	47%	10%	58%	24%
2008	249 984	116 388	25 004	144 431	59 208	47%	10%	58%	24%
2009	242 827	111 073	24 209	137 961	59 522	46%	10%	57%	25%
2010	241 871	108 385	24 437	135 074	59 685	45%	10%	56%	25%
2011	243 269	103 811	24 188	132 347	61 796	43%	10%	54%	25%
2012	246 015	104 380	23 950	131 250	62 973	42%	10%	53%	26%
2013	244 664	103 862	24 365	127 586	64 230	42%	10%	52%	26%
2014	240 677	102 695	24 407	124 823	63 419	43%	10%	52%	26%
2015	243 379	104 131	24 649	125 587	64 208	43%	10%	52%	26%
2016	244 421	104 915	24 886	125 404	64 217	43%	10%	51%	26%

Source: Own composition based on OIV (2019b).

It is evident that the consumption of wine products has globalised and the differences between the countries have decreased significantly. Thus, while consumption in producer countries decreased significantly, in non-producer countries, it increased drastically (from a low base).

Despite an increase in consumption during the period considered, production still exceeded consumption (by an annual average of 34 million hectolitres) each year. The surplus was mostly generated in Old Wine World countries (annually 47 million hectolitres on average).

1.3.4 Foreign trade

As explained in the previous point, the consumption of wine products has significantly globalised over the last 20-25 years. The data in Table 4 on world wine product exports illustrate well the pace of the changes.

Table 4

Worldwide exports of wine products, 1000 hectolitres, 1995-2016

Year	World	EU	3 Big	OWW	NWW	EU (%)	3 Big (%)	OWW (%)	NWW (%)
1995	55 016	38 341	33 646	46 592	6 722	70%	61%	85%	12%
1996	54 506	38 230	33 217	45 673	7 341	70%	61%	84%	13%
1997	60 551	42 374	37 121	50 084	8 565	70%	61%	83%	14%
1998	65 018	47 624	42 506	54 211	9 358	73%	65%	83%	14%
1999	63 979	48 737	43 779	53 466	9 567	76%	68%	84%	15%
2000	60 302	43 496	38 400	48 102	11 097	72%	64%	80%	18%
2001	65 151	46 327	40 961	51 488	12 659	71%	63%	79%	19%
2002	67 899	46 401	40 957	52 100	14 645	68%	60%	77%	22%
2003	72 501	48 013	40 820	53 900	17 270	66%	56%	74%	24%
2004	76 620	50 380	42 468	55 334	19 662	66%	55%	72%	26%
2005	78 978	51 778	44 151	57 264	20 244	66%	56%	73%	26%
2006	84 366	55 877	47 783	60 449	22 422	66%	57%	72%	27%
2007	88 951	58 696	48 296	61 104	25 841	66%	54%	69%	29%
2008	89 793	58 056	47 969	60 741	26 980	65%	53%	68%	30%
2009	88 238	56 374	47 286	59 306	26 950	64%	54%	67%	31%
2010	96 003	62 734	52 913	66 000	27 297	65%	55%	69%	28%
2011	103 377	70 940	60 630	74 373	26 294	69%	59%	72%	25%
2012	103 374	67 622	57 384	71 502	28 812	65%	56%	69%	28%
2013	101 737	63 624	53 604	67 423	30 915	63%	53%	66%	30%
2014	104 106	68 213	58 224	71 852	28 574	65%	56%	69%	27%
2015	105 659	68 766	59 022	72 290	30 116	65%	56%	68%	29%
2016	103 832	66 971	57 810	70 789	29 936	64%	56%	68%	29%

Source: Own composition based on OIV (2019b).

During the period analysed, the volume of wine exports increased significantly, by almost 90%, but at the same time somewhat changed. Although the main producing countries consistently accounted for 97-98% of total exports, the advancement of the New Wine World is very spectacular: New Wine World exports continued to grow steadily until 2010, and by 2016 had surpassed the baseline by four and a half times. In the meantime, exports from the Old Wine World countries increased by only 52% (75% for the EU Member States). By the end of the period, New World's share of world exports had risen from 12 to 29% (peaking at 31% during the economic crisis that started in 2008), while Old Wine World's share fell from 85 to 64%. The latter phenomenon concerned the three largest wine-producing countries only to a limited extent, with their share of exports falling by only 5 percentage points during the period considered.

In addition to the increase in the absolute volume of exported quantities, the change in the ratio of exports to production illustrates well the globalisation of the market for wine products (Table 5).

Table 5

Ratio of exported to produced quantity, 1995-2016

Year	World	EU	3 Big	OWW	NWW
1995	22%	25%	26%	25%	12%
1996	20%	22%	23%	22%	13%
1997	23%	27%	27%	26%	14%
1998	25%	30%	31%	29%	16%
1999	23%	27%	29%	26%	15%
2000	22%	25%	25%	24%	18%
2001	25%	30%	31%	28%	20%
2002	26%	31%	32%	29%	23%
2003	27%	32%	31%	29%	27%
2004	26%	28%	28%	27%	27%
2005	28%	31%	32%	31%	27%
2006	30%	33%	34%	31%	31%
2007	33%	36%	38%	34%	37%
2008	33%	36%	38%	34%	37%
2009	33%	35%	36%	33%	37%
2010	37%	41%	41%	38%	38%
2011	39%	45%	48%	42%	36%
2012	40%	46%	49%	44%	38%
2013	35%	37%	38%	36%	38%
2014	39%	43%	45%	42%	36%
2015	38%	41%	44%	40%	39%
2016	39%	41%	43%	40%	41%

Source: Own composition based on OIV (2019b).

On a global average, the volume of exports compared to the production increased by 78%. While, in 1995 two (slightly more) of ten bottles of wine products were consumed outside their country of origin, by 2016 (almost) four. Interestingly, this phenomenon applies uniformly to all groups of countries concerned.

1.3.5 Summary of global market trends

The picture of the world market for wine products has changed significantly over the last 20-25 years. First, production and then consumption has become global: more and more countries are producing and consuming wine products. Accordingly, the market share of Old Wine World traditional wine-producing countries (including those of the European Union) is steadily declining but is still significant. This period witnessed the success of the New Wine World, and in recent times additional new players have emerged (e.g. Chinese production has almost doubled and now exceeds that of Portugal or Germany).

As wine becomes global and wine consumption patterns change, local markets in wine-producing countries are shrinking, consumption is becoming more occasional, and consumption in new wine-consuming countries (typically from a very low base) is growing rapidly (for example, nearly three times non-traditional wine producers in EU Member States).

Meanwhile, the production volume itself and the difference between production and consumption did not change significantly.

As a result of the above, the world market for wine products is characterised by intense competition. The outcome of this competition is determined by two factors: the extent to which production costs are reduced and the extent to which prices are raised. In such a competitive environment, it is difficult to achieve higher prices, so it is crucial to exactly know the factors behind the price differences.

1.4 The market for wine products in Hungary

Hungary is one of the traditional wine-producing countries, where grape production and winemaking are very deeply embedded in society. In this chapter, I analyse the market of wine products in Hungary based on domestic data sources (Ministry of

Agriculture [AM], National Council of Wine Communities [HNT], Hungarian Central Statistical Office [KSH]).

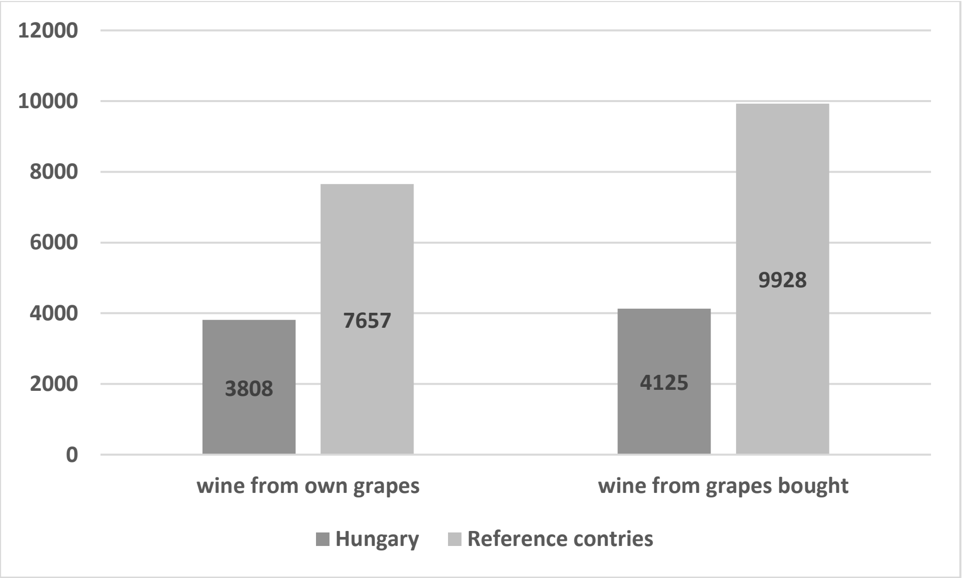
Figure 4 shows the production value per hectare of Hungary and some European wine-producing countries (the three large ones, Germany and Austria) expressed in euros/hectare (due to the methodology of statistical collection, data on winemaking from own or bought grapes cannot be compiled).

The share of the Hungarian grape and wine sector in the gross national product of agriculture is 2.6%, (KSH, 2017).

Currently, about 41,500 registered producers grow grapes in 6 wine regions and 22 wine districts[1] in Hungary (HNT, 2020, p.21). The wine products are marketed by about 6,000 registered wine producers with or without one of the 38 protected designations of origin or protected geographical indications (HNT, 2020).

Figure 4

The production value of the Hungarian grape and wine sector (euro/hectare) compared to the average of some European reference countries, 2011-2014



Source: HNT (2016 p.6)

[1] See Decree 127/2009 on the provision of information on viticulture and oenology and on the issuing of certificates of origin, as well as on the production, placing on the market and labelling of wine products (IX.29.) of the Ministry of Agriculture and Rural Development of Hungary.

1.4.1 Production of wine products

The volume of wine production is shown in Table 6.

The wine segment is fragmented, and the competition is fierce. A study by HNT (2020) finds that a significant proportion of active winemakers (59% in the wine year 2018/2019, a significant increase from 49% in 2014) does not market wine directly for public consumption, but sells it to other wineries as quasi-raw material.

Table 6

Production of wine products in Hungary, million hectolitres, 2008-2018.

Harvest year	Hungary	European Union	Share of Hungary
2008	3.45	172	2.01%
2009	3.20	165	1.94%
2010	1.97	157	1.25%
2011	2.72	156	1.74%
2012	2.10	140	1.50%
2013	2.56	163	1.57%
2014	2.59	156	1.66%
2015	2.47	170	1.45%
2016	2.65	162	1.64%
2017	3.18	138	2.30%
2018	3.64	189	1.92%

Source: Agrárminisztérium (2020).

The marketing of wine products was not concentrated, although the top 25 wineries marketed 66.5 %of all wine products in the wine year 2018/2019, due to the very low value of the Herfindahl-Hirschman index (3.73%).

1.4.2 Vineyard area

Table 7 shows the size and wine region distribution of the vineyards.

Table 7

Size of vineyards by wine region, hectare, 2012-2018.

Wine region	2012	2013	2014	2015	2016	2017	2018
Balaton	7 605	7 841	8 214	8 492	8 861	9 176	9 211
Duna	23 913	21 938	22 521	22 997	23 534	23 755	23 874
Felső-Magyarország	11 595	11 231	11 716	12 008	12 615	13 091	13 344
Felső-Pannon	4 881	5 228	5 257	5 390	5 433	5 568	5 492
Pannon	12 243	7 274	7 352	7 579	7 725	7 901	7 844
Tokaj	5 533	5 268	5 392	5 599	5 709	5 764	5 816
Total	**65 771**	**58 781**	**60 450**	**62 065**	**63 877**	**65 255**	**65 582**

Source: Agrárminisztérium (2020)

Hungary belongs to the group of small wine-producing countries both in terms of the size of the cultivated vineyards and the volume of wine production. Table 7 shows only a part, but the decrease of vineyards was a decisive trend until 2013 (HNT, 2020). This phenomenon was driven by the market (declining sales opportunities) and support policy reasons (EU subsidies for grubbing up vineyards). Subsequently, thanks in large part to the support of the restructuring program, which is also financed by EU funds, we are witnessing a slow increase in the area under vines.

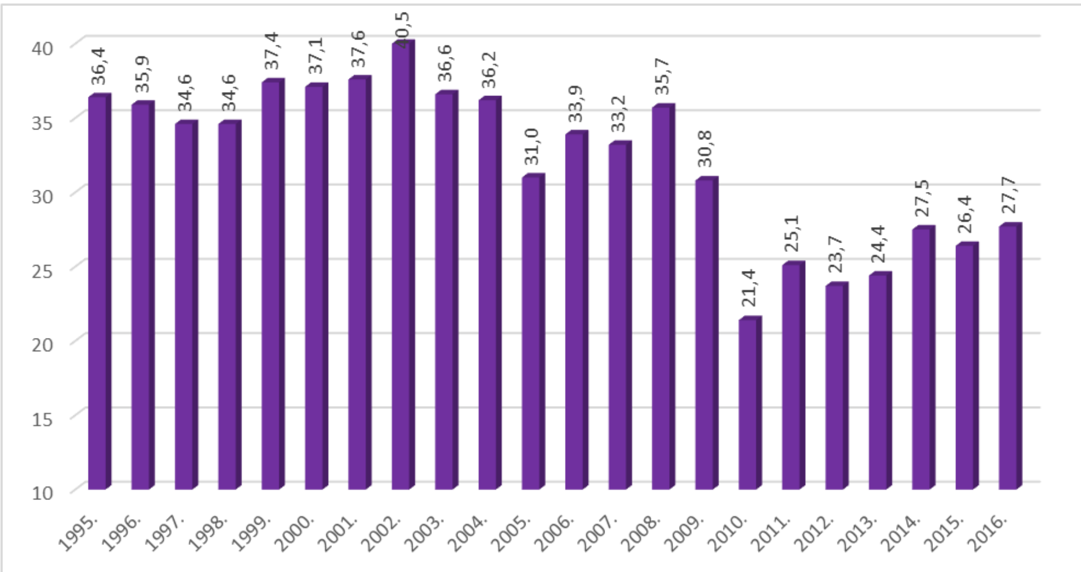
The average farm size of about 1.95 hectares (2017, median: 0.3860 ha) and the 0.07% value of the Herfindahl-Hirschman index (AM, 2020) show that viticulture is highly deconcentrated. The fact that more than four-fifths of the grapes produced is not processed into must or wine by the vineyard user (HNT, 2020 p.21) shows that the sector is vertically fragmented.

1.4.3 Consumption

Figure 5 shows the volume of per capita wine consumption in Hungary. Our country is not an exception from the traditional wine-producing and wine-consuming countries as consumption has also decreased in a 20-25 years perspective. However, it is noteworthy that the trend has been volatile but growing since 2010.

Figure 5

Wine consumption in Hungary, litre/capita, 1995-2016.



Source: Own composition based on OIV (2019b) data.

The characteristics of wine consumption in Hungary are summarised by the relatively recent market research[2] of Szolnoki and Totth (2019).

A representative survey of 1,200 people showed that Hungarians are very divided about wine consumption. 22% are regular wine drinkers (they drink wine at least once a week), while 34% of respondents never drink wine (usually the proportion of those who reject alcohol is similar, and wine is the least rejected alcoholic beverage) and 44% are occasional wine consumers.

Regular wine drinkers consume almost 75% of the amount sold (off-trade). The concentration of consumption is similar to other European countries. The proportion of men and older people is higher among regular wine drinkers.

The Hungarian wine market is respecting tradition in that 94% of the wines consumed are from Hungary, and 74% of wine consumers drink only Hungarian wine. The proportion of wine consumed from abroad is growing along with wealth status.

The Hungarian wine market is not considered an educated one; the average consumer is less interested in wine according to his own declaration, and (s)he knows relatively little about it. Both factors increase (improve) with the increase of age, wealth status, or wine consumption (and are higher than average for men).

1.4.4 Foreign trade

Looking at the foreign trade data (Table 8), we can see the picture of a net wine-exporting country. However, the situation is nuanced by the exceptionally high volume of imports in 2011 following the extraordinary crop loss in 2010 (see Table 6).

Over the past eleven years, the volume of exports has ranged from 532,000 to 1.28 million hectolitres, with a spectacular increase in volume between 2013 and 2018, but also followed by a decline in unit prices.

During the period considered, the unit price of exported wine products consistently exceeded the unit price of imports, although it was relatively low in international comparison. (HNT, 2020, p.24). This is because imports have long been dominated by raw materials at average prices very close to the European minimum price level, mainly from Italy. This practice began to gradually decline after 2014, to a practically minimal extent, as the average import price data for 2017 and 2018 suggest.

[2] The research treated wine and sparkling wines separately.

Table 8

Export and import of wines in Hungary, 2011-2018

Year	EXPORT Quantity (1000 hl)	EXPORT Value (million euro)	EXPORT Unit price (euro/litre)	IMPORT Quantity (1000 hl)	IMPORT Value (million euro)	IMPORT Unit price (euro/litre)
2008	694	73	1.05	259	23	0.89
2009	751	67	0.89	157	16	1.02
2010	861	76	0.88	199	17	0.85
2011	613	78	1.27	790	39	0.49
2012	757	74	0.98	553	39	0.71
2013	532	73	1.37	592	43	0.73
2014	706	80	1.13	455	28	0.62
2015	699	83	1.19	265	23	0.87
2016	760	90	1.18	255	22	0.86
2017	984	103	1.05	195	22	1.13
2018	1 284	124	0.97	72	17	2.36

Source: Agrárminisztérium (2020)

The decline in the unit price of exports may be of concern to the stakeholders in the sector, as it shows that a significant proportion of Hungarian wine products are more present in the lower price segments of the foreign markets. This means that the sales strategy is based on the low price of the product. In the light of the fragmentation of the supply side already shown (which suggests that production is not operating most efficiently), it is a vital threat, as import data show that these products can be produced much cheaper.

1.4.5 Geographical indications

Exploring the market positioning of geographical indications in Hungary is one of the most important goals of the present research; therefore, I consider it worthwhile to address their current status here as well. Nevertheless, a more detailed analysis of the situation of geographical indications in Hungary will be carried out in the light of the research results.

The fragmentation of the sector is also reflected in the diversity of production areas. Currently, 38 Hungarian GIs benefit from protection (31 designations of origin and 6 geographical indications are protected by the EU - 2 of which are temporarily protected and 1 is under conversion from a designation of origin to a geographical indication).

Table 9

Quantity of wine products marketed with geographical indications in Hungary, 2018

Geographical indication	Total quantity (hl)	Market share	Area planted with vines (ha)	Maximum yield of grapes (hl/ha)	Minimum sugar content (%vol)	Turnover share	GI type
Badacsony	14 576	0.44%	1 188	100	9.83	14%	PDO
Balatonboglár	44 446	1.34%	3 311	100	9.00	15%	PDO
Balaton-felvidék	2 946	0.09%	823	100	9.00	4%	PDO
Balatonfüred-Csopak	17 381	0.52%	1 946	100	9.00	10%	PDO
Bükk	1 682	0.05%	946	100	9.00	2%	PDO
Csongrád	1 228	0.04%	816	100	9.00	2%	PDO
Csopak	1 590	0.05%	120	63	10.60	23%	PDO
Debrői Hárslevelű	5 647	0.17%	529	100	9.83	12%	PDO
Duna	6 938	0.21%	12 733	100	9.00	1%	PDO
Eger	143 080	4.31%	5 248	100	9.83	30%	PDO
Etyek-Buda	33 410	1.01%	1 440	100	9.00	26%	PDO
Hajós-Baja	12 566	0.38%	1 471	100	9.00	9%	PDO
Izsáki Arany Sárfehér	227	0.01%	470	100	9.87	1%	PDO
Káli	804	0.02%	467	85	10.60	2%	PDO
Kunság	40 402	1.22%	11 156	100	9.00	4%	PDO
Mátra	52 812	1.59%	5 398	100	9.00	11%	PDO
Monor	365	0.01%	374	70	9.87	2%	PDO
Mór	3 837	0.12%	460	100	9.00	9%	PDO
Nagy-Somló	8 616	0.26%	456	100	9.00	21%	PDO
Neszmély	13 408	0.40%	920	100	9.00	16%	PDO
Pannon	15 871	0.48%	7 609	100	9.00	2%	PDO
Pannonhalma	13 440	0.40%	584	100	9.00	26%	PDO
Pécs	6 524	0.20%	537	100	9.00	13%	PDO
Soltvadkerti Ezerjó	101	0.00%	190	70	10.60	1%	PDO
Somlói	240	0.01%	367	80	11.34	1%	PDO
Sopron/Ödenburg	32 344	0.97%	1 562	100	9.00	23%	PDO
Szekszárd	58 669	1.77%	2 125	100	9.00	31%	PDO
Tihany	132	0.00%	78	63	10.97	3%	PDO
Tokaj	151 290	4.56%	5 618	100	9.00	30%	PDO
Tolna	23 972	0.72%	2 357	100	9.00	11%	PDO
Villány	91 493	2.76%	2 447	100	9.00	42%	PDO
Zala	1 923	0.06%	481	100	9.00	4%	PDO
Balaton	76 501	2.31%	8 565	120	8.00	8%	PGI
Balatonmelléki	49 333	1.49%	10 653	120	8.00	4%	PGI
Dunántúl	328 544	9.90%	21 353	160	8.00	11%	PGI
Duna-Tisza közi	1 278 978	38.54%	23 344	160	8.00	38%	PGI
Felső-Magyarország	349 653	10.54%	18 434	160	8.00	13%	PGI
Zemplén	5 327	0.16%	5 714	120	8.00	1%	PGI
Total with PDO/PGI	**2 890 296**	**87.09%**					
Without GI	428 293	12.91%					
Total	**3 318 589**	**100.00%**					

Source: Own composition based on Agrárminisztérium (2020)

There is no doubt about the diversity of places of origin in terms of numbers, but after reviewing the regulations of each GI, the question arises if this is happening in the right way. According to the HNT's (2020) assessment, in general, it is not, as local rules typically follow only a very low level of the national horizontal regulatory framework.

As the data in Table 9 show[3], there is a very large - and completely reasonable - difference between the total volume of wine products marketed with each geographical indication.

The PGIs with the three largest production areas account for about 60% of the supply and the proportion of wine products without a geographical indication provides a further 13%. Given that the production rules are the most permissible for these three PGIs (and for products without a geographical indication there are no such rules), it can be concluded that around 75% of the supply is positioned (in terms of geographical indications) to a particularly low level by producers.

This picture is somewhat complicated by the apparent fact that it is not only items that meet the minimum quality level rules that are marketed using these names[4].

Due to the outstanding market share of the three large PGIs, the Hungarian supply of wine products can be said to be concentrated in terms of GIs (the value of the Herfindahl-Hirschmann index is 19-23%, depending on the inclusion of wines without GI).

It is worth noting that the turnover rate (the ratio of the quantity actually marketed and the theoretical maximum – the maximum yield multiplied by the production area, adjusted for wine losses) is rather low (on average 13%, median 9-10% for PDOs and PGIs).

1.4.6 Summary of the Hungarian wine market

Overall, Hungary can be considered a traditional wine-producing and wine-consuming country, with a corresponding producer and consumer profile.

The supply is fragmented, and the market is highly competitive in all segments of the chain (viticulture, winemaking). Based on this, the export unit prices, and the structure

[3] Note: Table 9 does not show the quantity of new wine produced in a given year, but the quantity of wine actually marketed that year.
[4] Note: Medium-high and priced wine with one of the above geographical indications is also marketed under the author's name.

of the supply of geographical indications, a picture emerges of a sector that produces low value-added products with low efficiency in terms of good production conditions. The present dissertation does not focus on the complex development of the Hungarian grape and wine sector, but it can be mentioned that in this situation it is essential to increase the unit value of production to improve the profitability of the sector and thus ensure its economically sustainable development. All this is another reason why we should pay more attention to geographical indications when analysing the factors that explain wine prices.

2 LITERATURE REVIEW

The following chapter is a review of the literature on factors determining wine prices. First, I present the theoretical considerations that explain the existence of differences in wine prices. Next, I describe the method of identifying relevant articles, as well as some essential general criteria. Then, I turn to the structured presentation of the literature, grouped according to various factors. Finally, the chapter concludes with a critical analysis of the literature.

2.1 Theoretical background

Goods may be grouped into three categories based on the availability of information about their quality (Nelson [1970, 1974] and Darby and Karni [1973], Ford et al. [1988]). The first category is search goods, the quality of which, based on certain objective criteria, the consumer can conceive of before purchasing the product. The second is experience goods when the consumer can only assess the quality of the product after consuming it. The third category is the so-called credence products, the quality of which cannot be perceived by the average consumer either in advance or after consuming the good.

For this dissertation, accepting Storchmann's (2012) statement, I consider wine products as experience goods. However, classification as a credence product cannot be completely rejected, as many studies have already shown that the external characteristics of the products are decisive (vis-à-vis the inside) for the consumer. Veale and Quester (2008), in their focus group experiments, concluded that even the most sophisticated wine consumers do not appreciate the organoleptic properties of wines with reasonable certainty.

The classic of the market for experience products is Akerlof's (1970) example of the market of lemons (used cars). In markets where consumers lack adequate information on the quality, in theory, producers cannot charge a premium for their quality product, so only products of poor quality will remain on the market in equilibrium. As a result, high-quality products are pushed out of the market (as their sellers are not satisfied with the price), and only low-quality "lemons" remain.

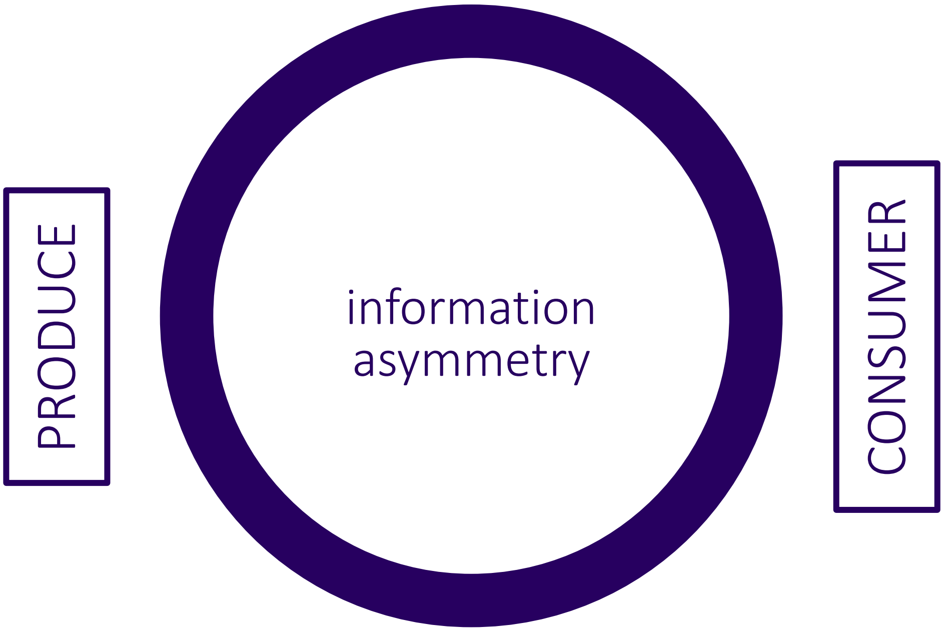
Nelson (1970) states that the cost of obtaining information on price and quality is quite different. Hence, there is a greater difference in the utility of quality between consumers than in the utility of price.

Therefore, if wine products are also considered as experience goods (since the consumer only knows what they receive for their money after consuming the wine), to achieve a price different (higher) from the market the key is to differentiate the products by dissolving information asymmetries on quality. This is practically achieved by informing the consumer (in most cases by labelling).

Credible differentiation of wine products can reduce (or even make it inelastic) the price elasticity of demand for them, as heterogeneity makes other products an imperfect substitute for differentiated products.

Figure 6

The market in wine products following Akerlof (1970)



Source: Own composition

The theory of monopolistic competition gives a reasonable explanation for the existence of price premia. "Monopolistic competition is a market structure in which there are many sellers supplying goods that are close, but not perfect, substitutes" (Samuelson and Nordhaus, 2010, p.668). The latter is the difference that separates monopolistic competition from perfect competition and the reason why each producer may affect their prices to some extent in those markets.

The starting point for location models - and their name suggests - is that each market player is necessarily located at some point in space and that geographical distance makes it difficult for consumers to substitute between different products. However, it is easy to see that this is also true in a tentative sense: each product is somewhere in the space of product characteristics, so the more the two products differ, the less substitutable one can be. Following the logic of Hotelling (1929), it can be stated that in the case of homogeneous goods, producers can achieve much lower prices than selling heterogeneous products.

In practice, this means that producers of individual products can achieve higher prices on the market than producers of virtually identical wines. In other words, if wines are to be considered as a commodity, producers must aim for standard flavours, but if they are experiential products, they must strive for uniqueness.

2.2 Identification of the relevant literature

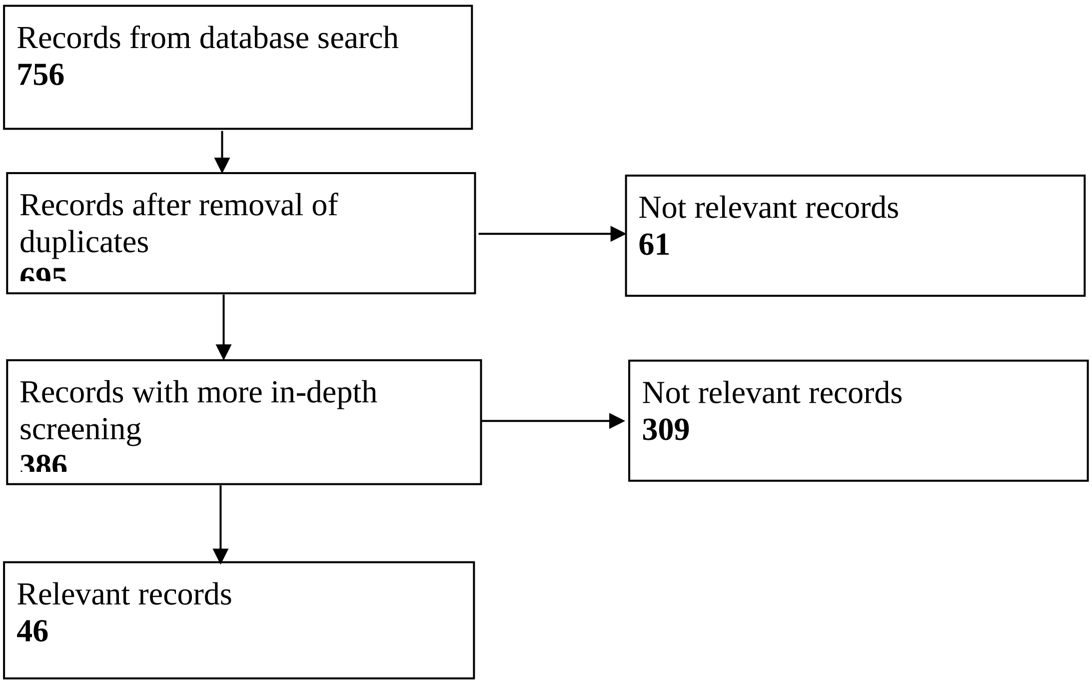
In order to get a comprehensive overview of the empirical findings on wine price determinants, a broad online search was conducted using the following databases: Web of Science, Scopus, JSTOR, ProQuest and Science Direct. The combination of keywords “wine” “price” “determinant” were used – these search items had to appear in the title, abstract or keywords of the sources.

The initial search resulted in 756 findings, and after removing duplicates, 695 entries remained. In order to ensure that only relevant articles are included in the final analysis, Covidence online software was used. All articles were screened independently by each author, and possible conflicts were then discussed personally. In the end, 46 articles remained.

Note that I adhered very strictly to the principle described above in the selection process, so I did not seek to increase the quantity of articles, but to identify quality articles that are truly closely related to the topic. I feel that at least half of the articles originally identified were about the relationship between consumer willingness to buy and wine prices, that is, about how consumers choose wines and to what extent purchasing prices are determined by the price of wine. It is clear that in these writings the price of wines appears as an independent and non-dependent variable (as would be justified by the topic of the present dissertation), so I omitted these articles from the sample. There were also plenty of articles on consumers 'willingness to pay, which I also did not consider relevant. The entire selection process is shown in Figure 7.

Figure 7

Process used to identify studies written on the determinants of wine prices



Source: Own composition

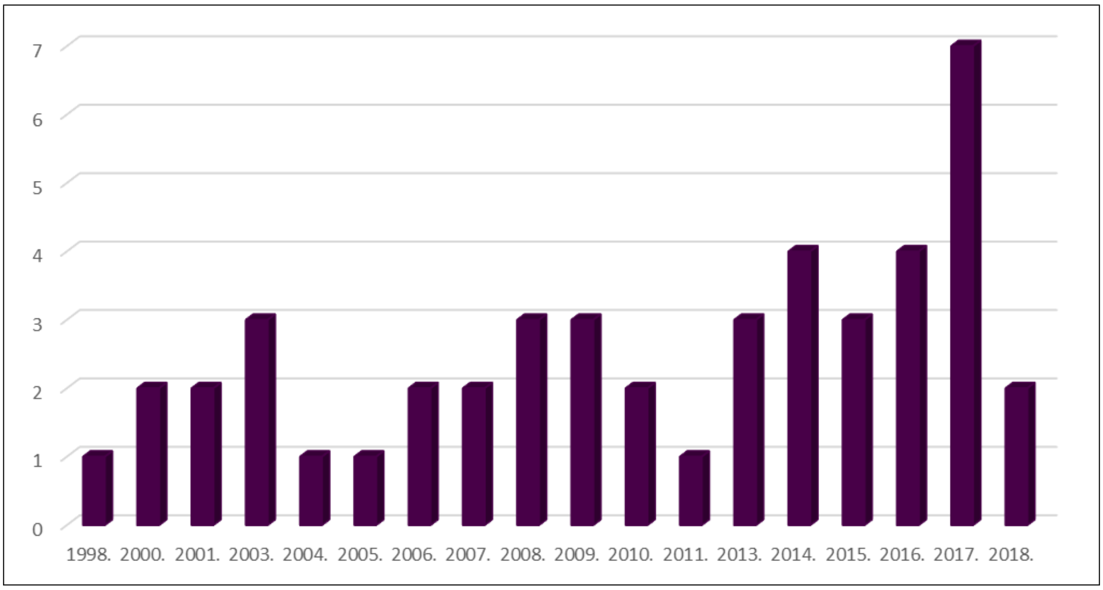
In order to review the Hungarian literature in a doctoral dissertation written in Hungary, including in Hungarian, I did a similar search on the MATARKA site in Hungarian. However, to my great surprise, the above search words did not return any results. On this basis, the conclusion is that no scientific research on the determinants of wine prices has been carried out in Hungary yet.

2.3 General characterisation and grouping of literature

Literature written on the determinants of wine prices is relatively new. The median publish year was 2012 and almost one fifth of them were published in 2017 or in 2018. Figure 8 shows the distribution of the examined literature by year of publication.

Figure 8

Relevant literature on the determinants of wine prices by year published



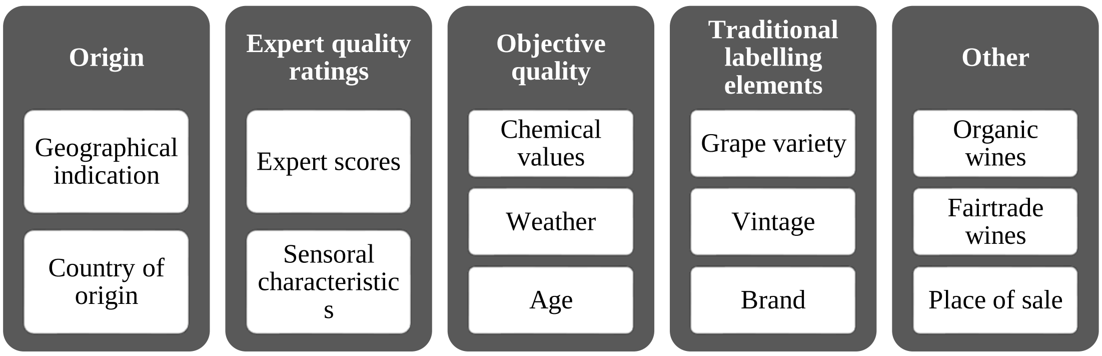
Source: Own composition

These articles were published in 31 different journals between 1998 and 2018 (the average is 1.5 articles/journal). Three journals had more than two articles in the sample: Journal of Wine Economics (five articles), International Journal of Wine Business Research (four articles) and Applied Economics (four articles).

Articles can be classified into five main categories (origin, expert quality ratings, objective quality, label data and other), giving the conceptual framework of our review (Figure 9).

Figure 9

Conceptual framework – The determinants of wine prices



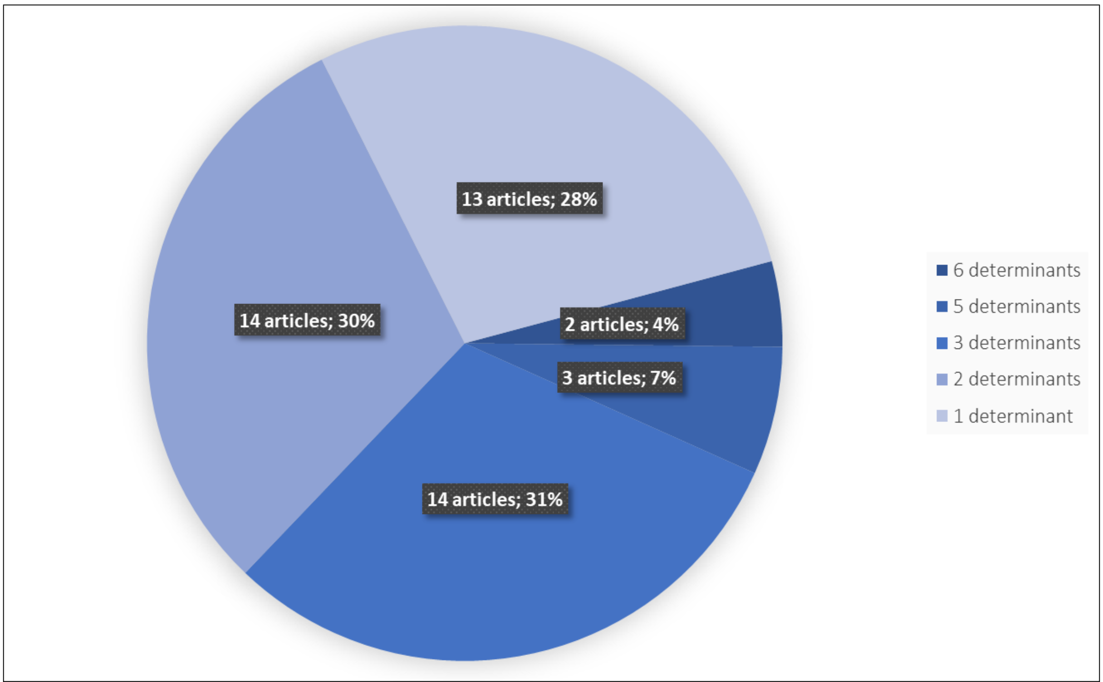
Source: Own composition

However, one article does not necessarily correspond to a single topic, as evident from Figure 9. An article generally deals with 2.4 of the above topics, while 17 articles analysed at least three determinants of wine prices. The 'hottest' topics were origin and expert ratings.

Note that is not possible to correspond all articles to one topic or another, as most of the read articles cover several topics, which is well illustrated in Figure 10. Accordingly, I mention an article separately for each topic concerned, always processing the relevant content there. One study examined the effect of an average of 2.4 factors on wine prices (median 2). Two articles stood out in this regard (Ling and Lockshin, 2003, and San Martín et al., 2008), which demonstrated the effect of 6 factors. For at least 3 factors, a total of 17 articles found a statistically significant correlation.

Figure 10

Literature written on the determinants of wine prices by the number of determinants analysed



Source: Own composition

Thus, some factors appeared in a larger, and others in a smaller proportion of the papers examined. In this regard, the origin plays the leading role (28 articles / 61% showed its significant impact), followed by expert ratings (27 articles / 59%), the traditional labelling elements (20 articles / 43%), and finally, by the objective quality characteristics (16 articles / 35%). A total of 10 articles (22%) justified the impact of other factors (22%). In addition to the professional arguments, the formation of the factor groups is well supported by their frequency, as all factors apart from the “other” appeared in 35-61% of the examined literature articles (with statistically significant impact on wine prices).

2.4 Origin

The place of production has always been an essential factor in the wine market, and accordingly, the practice of designating geographical names on wine labels has a long tradition. More than three-fifths of the literature (28 papers) included this topic and somehow confirmed the existence of this relationship.

Origin appears primarily on the label as a geographical indication (such as a wine region), but the country of origin is also listed here.

2.4.1 Geographical indications (place of origin)

Most of the examined papers (25) analysed the impact of geographical indications on prices.

Ali and Nauges (2007) analysed Bordeaux *en primeur* wine pricing on a sample of 1153 wines of 132 producers and showed that pricing behaviour of producers depends to a large extent on their place in the 1855 classification, and much less on short-term changes in quality (expert ratings). However, such classification systems are mainly effective in the markets of traditional wine-producing countries (continents). Blair et al. (2017) also reached similar conclusions regarding classification when analysing 393 Médoc (Bordeaux) wines of 1er, 2ème and 3ème Grand Cru Classé chateaux.

Angulo et al. (2000) concluded that origin was one of the most important determinants of wine prices by analysing 200 Spanish red wines, while Di Vita et al. (2015) also ended up in the same when analysing wine purchase of almost 2,000 households in Sicily (moreover, the impact of GIs rose with the rise of the prices – in contrast, the impact of individual brands on prices was found to be decisive for lower-priced products).

Ling and Lockshin (2003) studied the relationship between wine region area and wine prices for Australian wines and concluded that varieties in certain regions achieve higher price premium than in other regions. The similar conclusion was reached by Noev (2005) in the case of Bulgarian wines and Roma et al. (2013) for Sicilian wines using different variables for origin.

Moreover, the role of geographical indications was especially strong in price determination in case Burgundy wine sales in the British Columbia market (especially for villages, 1er crus and grand crus) as suggested by Carew and Florkowski (2010). The role of the place in the classification in Burgundy was echoed by Combris et al. (2000) studying 613 wines.

Levaggi and Brentari (2014) also underlined the importance of classification pointing out that comparing to IGT wines, the price premia of DOCG wines were significantly higher (33-43%) than DOC wines (7%). They added that geographic indication written on wine labels was more important in supermarkets than in specialised wine shops – its primary function was selection and not making the final decision.

Pucci et al. (2017), however, found that the role of geographical indications in price determination was rather country-specific and function of the consumers' awareness and experience with the actual wine.

A study by Arancibia et al. (2015) on the Argentinean market, examining 1015 wines, showed significant differences between wines from different administrative units.

Having examined 1750 Bordeaux wines, Ashton (2016) pointed out that the impact of production areas or geographical indications can differ even within a wine region as the impact of expert ratings proved to be much stronger on wines from right-bank (Pomerol, St. Émilion) producers, as in the case of the Left (Médoc, Pauillac).

Benfratello et al (2009) showed a 6.8% price difference between Barolo and Barbaresco wines on a sample of 603 wines.

In the case of the place of origin, the role of vineyard names (crus) as very small geographical units may be special. This argument was underpinned by San Martin et al. (2008) who analysed market possibilities for Argentine wines in the USA and concluded that vineyard names written on the label had a significant and positive effect on price.

Cardebat and Figuet (2004) analysed 26 Bordeaux geographical indications and 254 wines and concluded that regional reputation was a significant determinant of price. Their analysis of Alsatian, Provence and Beuajolais items on 140 samples (Cardebat and Figuet, 2009) partially supported this, with only 7 of the 22 GIs showing deviations from the average price.

Hay (2010), examining the Bordeaux en primeur market, concluded that expert ratings (Parker-points) and the 1855 classification influence prices on one another.

Landon and Smith (1998) analysed the collective reputation of Bordeaux red wines and found that reputation of seven out of eleven wine regions had a significant positive effect on price, which can even reach $14 per bottle. This strengthens the snob-effect where consumers prefer a bottle wine to another based on regional origin and reputation and not on quality difference.

Schamel and Anderson (2003) also showed a continuously increasing positive relationship between regional reputation and price, though this relationship was stronger in Australia than in New Zealand. Shane et al. (2018) estimated this price difference to be £6-7 for UK consumers.

Similarly, Thrane (2009) was talking about a 30% difference for French and German wines while Troncoso and Aguirre (2006) calculated 20% price difference for Chilean wines sold in the USA.

Ugochukwu et al. (2017) point out that the use of GIs leads to higher prices, but the converse is not true: the higher price of items is unrelated to the producer's decision of whether or not to use GIs.

Table 10 summarises the main findings of the articles examining the impact of GIs on wine prices.

Table 10

Summary of the literature studying the relationship of GIs and wine prices

Author	Topic	Country	Method	Results
Ali and Nauges (2007)	Effect of producer reputation and classification on price	France (Bordeaux *en primeur* and bottled)	Hedonic price index	Pricing is determined by the classification level to a great extent
Angolu et al. (2000)	Factors explaining Spanish wine prices	Spain	Hedonic price index	Origin (wine region) is one of the main price determinants
Arancibia et al. (2015)	Factors determining wine prices	Argentina	Hedonic price index	significant differences in prices due to origin (administrative units)
Ashton (2016)	comparing expert scores	France (Bordeaux en primeur, red)	Hedonic price index	effect of expert ratings varies according to origin
Benfratello et al. (2009)	relationship of expert ratings, reputation and prices	Italy (Barolo and Barbaresco)	Standard likelihood ratio model	significant difference between prices of the two GIs
Berrios and Saens (2015)	the impact of varietal specialisation on price	Napa, Sonoma, Oregon, Argentina, Australia, Chile, New-Zealand, South-Africa, Burgundy	Hedonic price index (OLS)	the price increased with specialisation in Napa and Oregon and decreased in Australia and New-Zealand
Blair et al. (2017)	brand equity and expert ratings	France (Médoc 1-3 GCC)	Compariso n of means	significant differences in prices at different classification levels
San Martín et al. (2008)	performance of Argentinean wines in the USA	Argentina	hedonic price index (2SLS)	indicating the name of the vineyard or the district has a positive impact on price
Cardebat and Figuet (2004)	Bordeaux wine prices	France (Bordeaux)	Hedonic price index (OLS)	reputation of origin is an important determinant of the price
Cardebat and Figuet (2009)	prices of Alsace, Beaujolais and Provence wines	France (Alsace, Beaujolais and Provence)	Hedonic price index (OLS)	origin is less important in this case
Carew and Florkowski (2010)	prices of Burgundy wines in British Columbia	France, Burgundy	Hedonic price index (panel)	GIs at higher classification levels have a serious impact on prices
Combris et al. (2000)	prices of Burgundy wines	France, Burgundy	Hedonic price index (OLS)	classification level of GIs impacts price
Di Vita et al. (2015)	prices of Sicily wines	Italy, Sicily	Hedonic price index (quantile regression)	GIs are the main price determinants, their impact increases with the price
Ferro és Amaro (2018)	factors explaining price of high-quality wines	USA	Hedonic price index (OLS)	origin (country and region) can impact price
Hay (2010)	role of wine critics	France (Bordeaux *en primeur*)	Hedonic price index (OLS)	expert ratings strengthen classification
Landon and Smith (1998)	The relationship of prices and quality in Bordeaux	France	Hedonic price index	Seven out of eleven regions have significantly positive impact on wine prices (+1-14 dollars)
Levaggi and Brentari (2014)	Factors impacting price of Italian wines	Italy	Hedonic price index	Indication of origin influences the price more in

				supermarkets than in wine shops
Ling and Lockshin (2003)	Factors determining wine prices	Australia	Hedonic price index	Varietals from certain regions have higher prices than from other regions
Noev (2005)	The relationship of price and quality	Bulgaria	Hedonic price index	Varietals from certain regions have higher prices than from other regions
Roma et al. (2013)	Factors determining Sicilian wine prices	Italy	Hedonic price index	The relationship of origin and prices is significant and positive
Pucci et al. (2017)	Study on the relationship of origin and prices	Italy	Logistic regression	Origin significantly (and positively) determines the price of a wine
Schamel and Anderson (2003)	Factors determining prices of wines of Australia and New-Zealand	Australia and New-Zealand	Hedonic price index	The relationship of origin and prices is significant, positive and increasing
Shane et al. (2018)	Factors of prices of Australian wines in the United Kingdom	Australian wines in the United Kingdom	Hedonic price index	The relationship of origin and prices is significant and positive
Thrane (2009)	Study of subjective and objective factors of wine prices	Germany, France	Hedonic price index	The difference between prices of wines with different origin is significant
Troncoso and Aguirre (2006)	Factors of Chilean wine prices in the USA	Chile, USA	Hedonic price index	The relationship of origin and prices is significant, positive and increasing
Ugochukwu et al. (2017)	Questions on qualification of Canadian wines	Canada	Probit	All in all, the use of GIs impacts positively wine prices

Source: Own composition

All in all, every item of the literature found positive relationship between origin and wine prices.

2.4.2 Country of origin

Five of the articles examining the relationship between the origin and price found a link with the country of origin (COO – Table 11).

Arias-Bolzmann et al. (2003) on a sample of 420 wines from seven countries showed a significant difference in the effect of some countries on prices. While French wines were significantly more expensive (43%) than the comparative Californians, in South Africa (-23%) and Chile (-40%) this effect was precisely the opposite.

Berrios and Saens (2015), focusing on the relationship between origin and grape variety, observed the effect of specialisation on prices (i.e. if a wine region or country focuses on a single product [variety]) by observing price dynamics over six vintages.

The results were mixed, finding that this step was rewarding for Napa Valley, California, and not for Australia and New Zealand.

Ferro and Amaro (2018) examined the effect of origin on relatively limited prices in their analysis of 1,400 items on the US market.

Hoang et al. (2016) showed that the price premium of foreign organic wines is significantly higher than that of Japanese by examining 1,682 items on the Japanese market.

Pucci et al. (2017) showed that in some markets, the influence of the country of origin is more important than that of the wine region.

Table 11

Summary of the literature studying the relationship between country of origin and wine prices

Author	Topic	Country	Method	Results
Arias-Bolzmann et al. (2003)	Factors impacting wine prices	USA	Hedonic price index	French wines are significantly more expensive than the average, South Africans and Chileans are significantly cheaper
Berrios and Saens (2015)	The effect of the specialization of a region (the advancement of a variety) on price	Napa, Sonoma, Oregon, Argentina, Australia, Chile, New-Zealand, South Africa, Burgundy	Hedonic price index (OLS)	The price has increased for Napa and Oregon and the price has decreased for Australia and New Zealand with specialisation
Hoang et al. (2016)	Analysis of the domestic and imported organic wine market	Japan	Hedonic price index (OLS)	The price premium for imported organic wines is higher in Japan
Ferro and Amaro (2018)	Factors explaining the price of high quality wines	USA	Hedonic price index (OLS)	The place of origin (country) can affect the price
Pucci et al. (2017)	Examining the relationship between production and wine prices	Italy	Logistic regression	In some markets, the impact of the country of origin is more important than that of the wine region

Source: Own composition

2.5 Expert ratings

The informative power of expert ratings assumes that some experienced, recognized, qualified wine experts can accurately assess the quality of the wines (either the character or the quality level). The reputation of the expert who carries out the qualification plays a major role in the credibility of the expert sensory ratings (Masset et al., 2016). Among the literature examining the effect of expert ratings, I found an example of taking into account both dimensions of wine quality (quality level, character).

2.5.1 Quality level (points)

Ali et al. (2008) analysed 300 Bordeaux *en primeur* wines and found that an extra Parker score meant €2.8 more per bottle, though this effect is non-existent for low-scored wines.

Angulo et al. (2000) also found a positive relationship between quality ratings and price for Spanish red wines and concluded that the odds for a wine to present a medium or a high price (instead of a low one) increased by 1.52 and 2.44 times, respectively, with a one-point increase in the quality rating.

Arias-Bolzmann et al. (2003) also supported the idea above – by analysing *Wine Spectator*'s lists, they found a single point increase to result in a 5.2% price growth. Ashton's (2016) research examining sales in Bordeaux *en primeur* examined the difference between the effects of points given by different experts. He found that Robert Parker's scores have a significantly higher impact on price than Jancis Robinson's expert rating, but the two together produce the greatest impact (explanatory power of models with only Parker's scores is higher than that of Robinson's scores only, but explanatory powers of individual models are lower than the model with scores from both experts).

Benfratello et al. (2009) model of Barolo and Barbaresco wines showed the effect of sensory evaluations resulting in an 8–11% price increase (which, however, lags behind the effect of individual brands).

Blair et al. (2017) found in a sample of Médoc wines that there was a very significant price difference between the prices of 100-point wines that Parker considered perfect and the prices of wines that did not reach 100 points.

San Martin et al. (2008) used a two-step least squares method in their analysis of the performance of Argentine wines in the US market, interpreting the effect of other factors (e.g. origin, harvest year) as instruments of expert ratings (assuming that their effect is also reflected in expert ratings). They pointed out that expert ratings had a significant effect on price: an extra point raises it by 4.5%.

In a sample of Bordeaux wines, Cardebat and Figuet (2004) showed a 0.44% higher price associated with a 1% increase in expert ratings. The same was not supported by their analysis of a sample of Alsatian, Provencal and Beuajolais items (Cardebat and Figuet, 2009), they showed a significantly weaker relationship between expert ratings and price: at a significance level of 10%, 0.29% increase in the expert ratings resulted in a price increase of 1%.

Combris et al. (2000) developed several hedonic models to avoid endogeneity, and not all of the models explaining price took into account the total score of sensory criticism. The presence of endogeneity is indicated by the fact that most variables are significant in all models. However, this does not pose a significant practical problem in this case, as the results of the models with and without the total evaluation score are similar and the same conclusions can be drawn from them. Expert ratings (on a 20-point scale) were performed for both the current state of the wines examined and their future potential. The difference between the two values is equal to the development potential of the items. Their main finding is that an extra point in an expert rating of the current condition results in a 2.4% higher price, while for development potential, this value is 8.4%.

Ferro and Amato (2018) analysed the TOP100 list of *Wine Spectator* for 14 years and found that a 1% increase in expert ratings resulted in a 14.1% wine price increase. Haeger and Storchmann's (2006) study of California and Oregon pinot noir wines found the explanatory power of expert ratings to be low (the explanatory power of the models studied barely increased with the inclusion of this variable), while they estimated a significant 4.2-7.6% by which an extra point affects the price.

Hay (2010), after examining *en primeur* sales in Bordeaux, found that Robert Parker's expert ratings reinforced the price differences associated with the classification system.

Jones and Storchmann (2001) also examine, among other things, the effect of Parker points on the prices of quality wines in Bordeaux and conclude that for wines dominated by Cabernet Sauvignon, subjective quality factors play a significant role in prices, while for Merlot-dominated wines, the role of subjectivity is lower.

Kwong et al. (2017) examined the relationship between expert scores and wine prices for dry red wines in Canada and found that a one point growth in expert scores increases the price of a wine by an average of 4%, all other factors being constant.

A similar result was reached by Troncoso and Aguirre (2006), who examined the determinants of 2603 Chilean wine prices in the U.S. market between 1979 and 2002. According to their results, an expert score increase made the price of the wines examined by an average of 3.5% to grow.

Ling and Lockshin (2003) estimated the effect of the scores given by the experts separately for wines for warm and cool climates. In both cases (and in the joint analysis of the two subsamples), the results showed a positive, significant relationship (+12.5% of the total sample), which is higher in the case of warmer climates (+14.5% and +8.6%, respectively).

Masset et al. (2016) examine the price premium of Bordeaux wines sold at auctions held in Hong Kong and conclude that wines with higher Parker points can also be sold at higher prices.

Examining the relationship between the prices and quality of Bulgarian wines, Noev (2005) also pointed out that the result of expert sensory evaluation had a significantly positive relationship with price. According to his results, this relationship is extremely strong, wine rated 1 point higher can be sold at a price almost 0.8% higher.

Oczkowski and Doucouliagos (2014) examined the relationship between wine prices and expert ratings using a literature model of 180 models and concluded that there was a moderately strong relationship between wine prices and organoleptic quality in the majority of the literature. According to their results, wineries should strive to achieve the best possible results based on organoleptic tests through their quality products, as this is the basis of their livelihood.

Roma et al. (2013) reach a similar conclusion when examining samples of Sicilian wines with 609 and 410 elements. According to their results, there is a significant and positive relationship between wine prices and sensory evaluation in both samples. Their results also show that the role of aroma is high, while taste is low in determining the prices of wines - in other words, consumers are willing to pay more for wines with spicy aromas.

Frick and Simmons (2013) examined the relationship between wine prices and expert ratings through nearly 1,300 Riesling wines from 70 wineries in the Mosel Valley (Germany) and found that although the relationship between the two was significant but not as strong as it was when farmers came together and sold their wines together through professional organisations (in the latter case, the effect on prices was stronger).

Table 12

Summary of the literature examining expert ratings describing wine prices and wine characteristics (quality level)

Author	Topic	Country	Method	Results
Abraben et al. (2017)	The impact of organic winemaking certification on wine prices	Italy	Hedonic price model	The price differences between the different organic and conventional wines are smaller among the items with a high expert sensory rating
Ali et al. (2008)	The effect of expert ratings on price	France (Bordeaux *en primeur*)	Stable unit treatment, difference in differences	An extra Parker point raises the price of a bottle of wine by €2.80
Angulo et al. (2000)	Factors explaining Spanish red wine prices	Spain	Hedonic price model	The chances of achieving a higher price are increased by orders of magnitude by a higher expert rating
Arias-Bolzmann et al. (2003)	Factors affecting wine prices	USA	Hedonic price model	A higher expert rating is coupled with higher prices
Ashton (2016)	Comparison of expert ratings	France (Bordeaux en primeur, red)	Hedonic price model	Higher expert rating coupled with higher prices; Parker's influence is greater than Robinson's
Benfratello et al. (2009)	The relationship between expert qualification, reputation and prices	Italy (Barolo and Barbaresco)	Standard likelihood ratio model	The positive effect of expert qualification can be demonstrated, but it lags behind the effect of individual brands
Blair et al. (2017)	Brand value in light of expert sensory reviews	France (Médoc 1-3 GCC)	Comparison of averages	The price of wines considered perfect (100/100 points) is significantly higher than the others
San Martín et al. (2008)	The performance of Argentine wines in the U.S. market	Argentina	Hedonic price model (2SLS)	An extra point in the expert ratings increases the price by 4.5%
Cardebat and Figuet (2004)	Prices of Bordeaux wines	France (Bordeaux)	Hedonic price model (OLS)	1% increase in expert ratings increases the price by 0.44%
Cardebat and Figuet (2009)	Prices of Alsatian, Beaujolais and Provencal wines	France (Alsace, Beaujolais, Provence)	Hedonic price model (OLS)	The relationship between rating and price is very weak
Combris et al. (2000)	Prices of Burgundy wines	France – Burgundy	Hedonic price model (different OLS models)	Expert rating is positively related to price: an extra point means a higher price of 2.4%, while the impact on the development potential of the wine is higher
Ferro and Amaro (2018)	Factors explaining the prices of WS TOP100 wines	USA	Hedonic price model (OLS)	1% increase in expert ratings means a 14% higher price

Haeger and Storchmann (2006)	Price of pinot noirs produced in California and Oregon	USA	Hedonic price model (OLS)	The effect of expert ratings is significant (4.2-7.6%), but its explanatory power is low
Hay (2010)	Bordeaux en primeur sales and expert reviews	France, Bordeaux	Hedonic price model (OLS)	Expert ratings confirm the effect of the classification system on price
Jones and Storchmann (2001)	Determinants of wine prices in Bordeaux	France	Hedonic price model	Parker points have a serious effect on price for cabernet sauvignon-dominated wines, while less so for merlot-dominated wines.
Kwong et al. (2017)	Factors determining wine prices in semi-parametric models	Canada	Hedonic price model	There is a significant and positive relationship between expert scores and Canadian dry red wine prices (+ 4%)
Troncoso and Aguirre (2006)	Factors determining the price of Chilean wines in the US	Chile, USA	Hedonic price model	There is a significant and positive relationship between expert scores and Chilean wine prices (+ 3.5%)
Ling and Lockshin (2003)	Factors determining wine prices	Australia	Hedonic price model	Expert scores are positively related to price (+ 12.5%), the effect is greater in warmer climates
Masset et al. (2016)	Characteristics of the Chinese quality wine market	China	Hedonic price model	Higher Parker scores result in a significant and positive price premium
Noev (2005)	The relationship between wine prices and quality	Bulgaria	Hedonic price model	Wine rated 1 point higher can be sold at a price almost 0.8% higher
Frick and Simmons (2013)	Relationship between reputation and wine prices	Germany	Panel regression	The relationship between wine prices and subjective quality is positive, but less strong than the impact of professional organisations on price
Oczkowski and Doucouliagos (2014)	The relationship between wine prices and quality	global	Literature review	There is a moderately strong relationship between wine prices and organoleptic quality
Roma et al. (2013)	Determinants of Sicilian wine prices	Italy	Hedonic price model	There is a significant and positive relationship between wine prices and sensory rating
Schamel and Anderson (2003)	Factors Determining Australian and New Zealand Wine Prices	Australia, New-Zealand	Hedonic price model	1 point higher rating is coupled with a 0.5-1 Australian dollar higher price
Sinpes and Taylor (2014)	Applying the Akaike information criterion to the relationship between wine prices and valuations	global	Akaike information criterion	There is a significantly positive relationship between wine prices and subjective rating
Thrane (2009)	Examination of objective and subjective factors determining the price of wines	Germany, France	Hedonic price model	The price of wines is determined by expert ratings rather than objective quality

Source: Own composition

However, Schamel and Anderson (2003) found a particularly strong relationship between wine prices and sensory ratings when examining wine prices in Australia and

New Zealand – a 1-point improvement in valuation resulted in a price increase of 0.5-1 Australian dollars.

Snipes and Taylor (2014) examined the relationship between expert ratings and price of wines for 197 wines in the *Wine Spectator* database using Akaike's information criterion model, and also came to what the majority of the literature has done so far: the relationship is significant and positive. Another interesting new result is that, based on their pattern, Chardonnay wines always get relatively higher scores for some reason, but the reasons for this have not been examined in the article.
Overall, it can be concluded that the vast majority of articles found a significant and positive relationship between wine prices and expert ratings (scores), however, opinions differ on the strength of the relationship.

2.5.2 Character (wine descriptions)

The research of Arancibia et al. (2015) on the Argentine wine market also addressed the effect of sensory characteristics on price. They found that the publication of wine descriptions on the label had a negative effect on the price of low-priced wines (-0.8%), a positive effect on the price of high-priced wines (18.2%), but the complex effect is negative (-7.7%).

Combris et al. (2000), in a sample of Burgundy wines, showed that some sensory characteristics (excessive acidity, body, concentration) were significantly related to price. The direction of relationship is positive except for excessive acidity.

Levaggi and Brentari (2014) found that some organoleptic properties (colour, spiciness, taste length) to be significantly positively related to price, but there was also a negative effect (purple - this is the characteristic of young, less matured red wines). The extent of the effect also depends on the distribution channel, being larger in large grocery stores than in wine stores.

Thrane (2009) draws similar conclusions by examining the prices of 212 German and French wines and their determinants. The author concludes that expert rating (information about wine character) determines wine prices more than objective parameters. However, the author also notes that a lot depends on exactly what models are used to test the relationship between the variables examined. The study showed that an extra point for corporality was coupled with 21% higher price, while an extra score for freshness increased prices by 11%. Results are summarised in Table 13.

Table 13

Summary of the literature examining expert sensory qualifications describing wine prices and wine characteristics (character)

Author	Topic	Country	Method	Results
Arancibia et al. (2015)	Determinants of wine prices	Argentina	Hedonic price model	The publication of wine descriptions on the label has a negative effect on the price of low-priced wines and a positive effect on the price of high-priced wines
Combris et al. (2000)	Prices of Burgundy wines	France – Burgundy	Hedonic price model (multiple OLS models)	Some elements of the wine character are significantly related to price
Levaggi and Brentari (2014)	Factors affecting Italian wine prices	Italy	Hedonic price model	Some sensory properties have a positive effect on the price, while the extent of the effect also depends on the distribution channel
Thrane (2009)	Objective and subjective characteristics determining wine prices	Germany, France	Hedonic price model	The price of wines is determined by expert sensory rating rather than objective quality

Source: Own composition

2.6 Objective quality

Factors classified into the group of objective (inner) quality characteristics, unlike the organoleptic qualities, can be easily quantified. having examined the literature, three such factors were identified: chemical composition, the weather of the harvest year, and the age of wines.

2.6.1 Chemical composition

The chemical components of wines are important elements of measurable quality characteristics. With the development of instrumental analytics, the concentrations of numerous components became easily and quickly measurable. However, in most cases, the magnitude of the alcohol, sugar content, acidity and sulphite contents matter. The main findings of the articles described are summarised in Table 14.

In terms of chemical composition, Arancibia et al. (2015) analysed Argentinean wines and showed that a 1% increase in alcohol content was associated with a 10.3% increase in price (however, when repeating the model runs for high and low-quality wines, 6.8% and 5.2% changes were found, respectively). Roma et al. (2013) reached similar conclusions and found that a 1% of alcohol content growth meant a 7-10% price increase for Sicilian wines.

By examining the effect of the chemical characteristics of Italian red wines (actual alcohol content, residual sugar content, volatile acidity, total acidity, sulphur dioxide content, and the ratio of free and bound sulphur content) on prices, Levaggi and Brentari (2014) concluded that they have significant positive effect prices.

Table 14

Summary of the literature examining the chemical components that determine wine prices

Author	Topic	Country	Method	Results
Angulo et al. (2000)	Determinants of Spanish red wine prices	Spain	Hedonic price model	The alcohol content shows no correlation with price
Arancibia et al. (2015)	Determinants of wine prices	Argentina	Hedonic price model	The effect of alcohol content on the price is positive (on average 10.30%)
Roma et al. (2013)	Determinants of Sicily wine prices	Italy	Hedonic price model	The effect of alcohol content is positive on the price (on average 7-10%)
Levaggi and Brentari (2014)	Determinants of Italian wine prices	Italy	Hedonic price model	All measured factors have a significant positive effect on prices
Thrane (2009)	Examination of objective and subjective factors determining the price of wines	Germany, France	Hedonic price model	Alcohol content and sugar content have a positive but mutually limiting effect on wine prices

Source: Own composition

On the contrary, Angulo et al. (2000) did not find any relationship between alcohol content and prices of Spanish wines. In a sample of German and French wines, Thrane (2009) showed a significant effect of chemical ingredients on price. One percentage point higher alcohol content (depending on the model specification) results in 11.3-30% higher price, while one percentage point higher sugar content means 0-4.8% higher wine price. However, the effect of the two components dampens each other, as their cross-effect has a price-reducing impact (-0.4%).

At the same time, we can state that the chemical composition of wine affects the price of wines.

2.6.2 Weather of the harvest year

The weather of the harvest year (vintage) is one of the four main factors affecting wine quality. In this section, I describe the effect of factors describing the vintage from a meteorological point of view.

Ashenfelter (2008) analysed Bordeaux wine characteristics and prices and found that precipitation levels before the growing season and during harvest had significant impacts on wine prices. These effects, however, are ambiguous as expected – a millimetre growth in rainfall during harvest season decrease prices by 0.4%, while before the growing season, it increases prices by 0.12%.

Table 15

Summary of the literature examining the weather characteristics that determine wine prices

Author	Topic	Country	Method	Results
Jones and Storchmann (2001)	Determinants of wine prices in Bordeaux	France	Hedonic price model	For Bordeaux wines, there is a significant relationship between weather and prices
Ling and Lockshin (2003)	Determinants of wine prices	Australia	Hedonic price model	Improving the quality of wines from warmer regions entails a higher price premium than increasing the quality of wines from cooler regions
Ashenfelter (2008)	Forecasting the quality and price of Bordeaux wines	France	Hedonic price model (OLS)	The amount of precipitation is significantly related to the price (negative or positive depending on the time of fall), the effect of temperature is not significant
Chevet et al. (2011)	The relationship between wine prices, production and weather	France	Time series	Weather is having an increasing impact on wine prices
Haeger and Storchmann (2006)	Price of pinot noirs produced in California and Oregon	USA	Hedonic price model (OLS)	Temperature and precipitation have the greatest impact on wine prices

Source: Own composition

Jones and Storchmann (2001) found that as dry and warm summers made Bordeaux wines richer in sugar content (and higher in quality) and thereby increased their prices.

However, they also found Merlot dominated (Right Bank) wines to be more sensitive to weather than Cabernet Sauvignon dominated (Left Bank) ones, causing prices of the former to be more volatile.

Haeger and Storchmann (2006) found that for Pinot Noir grown in the USA, temperature and precipitation were the main weather-related drivers of prices.

Ling and Lockshin's (2003) study did not classically consider the weather of the harvest year, but the climate of a given region. Their results show that an improvement in the quality of wines from warmer regions entails a higher price premium than an increase in the quality level of wines from cooler regions.

Chevet et al. (2011) examined the long-run relationship between weather and wine prices (1800–2009) for Bordeaux wines. It has been found that weather is having an increasing impact on wine prices as quality is considered.

The main findings of the articles examined are summarised in Table 15. We can therefore conclude that, based on the above, weather is also an important influencing factor of price.

2.6.3 The age of the wine

Public belief holds that wines will only get better and better over time. Although this finding is not true, the study of the relationship between the age of wine and the price has aroused the interest of many authors.

In connection with the study of the age of wines, Ali et al. (2008) in a sample of 250 elements in Bordeaux demonstrated that the age and price of wine are related, however, the price premium of age varies according to the judgment of the vintage concerned and may even be negative.

Arias-Bolzmann et al. (2003) analysed 420 wines from seven countries and showed that a single year of age means 7% of price increases on average.

Ashenfelter (2008) showed a positive but relatively weak relationship between age and price for Bordeaux wines. Each additional year increases the price by 3.5%, however, the explanatory power of the model containing only the age of wine was relatively low.

In their article, Jones and Storchmann (2001) also examined the relationship between age and prices of Bordeaux wines and concluded that there was a significant positive relationship between the two factors. This is due, on the one hand, to the maturation, which means an objectively measurable and perceptible richness of taste, and, on the other hand, to the rarity, i.e. there are already fewer older wines on the market. There are also costs associated with storing larger quantities of older wine, which also increases prices. The authors also find that, for wines made of Merlot, maturation is more cost-effective than Cabernet Sauvignon-dominated (Left bank) wines.

Ling and Lockshin (2003) reached similar conclusions, with regard to Australian wines, showing that wines younger than 8 years can be sold at 8-14% k lower prices than wines older than 8 years. Noev (2005) also found a significantly positive relationship between wine prices and the age of wines, however, results here suggest that this relationship can only be detected for red wines in Bulgaria.

San Martin et al. (2008) found that age affects the price of wines, however, the relationship is not linear, the price of wine rises to the age of 19, from there it decreases.

Shane et al. (2018) reached similar conclusions when looking at the prices of Australian wines sold in the UK – each surplus of wine raises prices slightly by 0.8%.

Thrane (2009), measuring the relationship between the age and price of wines with a quality variable, found that the price of wines from 2003 or earlier vintages is 12–30% higher than that of younger ones. The studies of Troncoso and Aguirre (2006) also supported the association between the price and age of wines. According to their results, among Chilean wines sold in the US, the age of a year results in an average price increase of 5.6%.

In the case of Porto wines, Viana and Rodriguez (2007) showed that there was a fundamentally significant and positive (2-3%) relationship between the age and price of wines, while the prices of 30-40-year-old wines can be 100-200% higher.

The main correlations between the age and price of wines are shown in Table 16. It is clear that the age of a wine has a fundamentally price-increasing effect.

Table 16

Summary of the literature on the relationship between wine prices and age

Author	Topic	Country	Method	Results
Jones and Storchmann (2001)	Determinants of wine prices in Bordeaux	France	Hedonic price model	There is a significant positive relationship between the age and prices of Bordeaux wines
Ling and Lockshin (2003)	Determinants of wine prices	Australia	Hedonic price model	Wines younger than 8 years old can be sold at 8-14% lower prices than wines older than 8 years old
Noev (2005)	Relationship between wine prices and quality	Bulgaria	Hedonic price model	There is a significantly positive relationship between the price and age of red wines
Shane et al. (2018)	Determinants of Australian wine prices in the UK	Australia, United Kingdom	Hedonic price model	There is a moderately positive relationship between wine prices and the age of wine
Ali et al. (2008)	The effect of expert sensory rating on price	France (Bordeaux *en primeur*)	Stable unit treatment, difference in differences	The correlation between price and age is positive
Arias-Bolzmann et al. (2003)	Determinants of wine prices	USA	Hedonic price model	There is a significantly positive relationship between the price and age of wines
Ashenfelter (2008)	Forecasting the quality and price of Bordeaux wines	France	Hedonic price model (OLS)	Age is significantly (positively) related to price
San Martín et al. (2008)	The performance of Argentine wines in the U.S. market	Argentina	Hedonic price model (2SLS)	The relationship between age and price is quadratic
Thrane (2009)	Examination of objective and subjective factors determining the price of wines	Germany, France	Hedonic price model	Wines from the 2003 vintage or earlier are 12-30% more expensive
Troncoso and Aguirre (2006)	Determinants of Chiliean wine prices in the USA	Chile	Hedonic price model	Wines a year older are on average 5.6% more expensive
Viana and Rodriguez (2007)	Determinants of Oporto wine prices	Portugal	Hedonic price model	A year older wine costs on average 2-3% more

Source: Own composition

2.7 Other traditional labelling elements

In the following section, I present the literature examining the role the most (traditionally) popular labelling elements on wine prices besides origin. These items include grape variety, vintage and individual brands.

2.7.1 Grape variety

The grape variety is one of the determinants of wine quality, playing a major role in some markets as it conveys quality standards that are easy for consumers to understand. Since one of the defining elements of a grape variety is its colour, I also discuss the results related to the colour of wine among grape varieties.

Kwong et al. (2017), for instance, showed that prices for Syrah, Cabernet Franc, Cabernet Sauvignon, Merlot, Pinot Noir and Baco wines were significantly higher than any other types in Canada.

Ling and Lockshin (2003) supported this view and suggested that Shiraz and Cabernet wines sell better than Chardonnay-based wines.

However, examining the prices of Bulgarian wines, Noev (2005) pointed out that local trends tended to increase the consumption of white wine and found that the prices of white wines were fundamentally higher than the prices of traditional Bulgarian red wines.

A similar conclusion is reached by Ferro and Amato (2018), who examined wines listed in the *Wine Spectator TOP 100* list between 2003 and 2016 in the U.S. market. According to their results, among other things, the price of white wines is 10-16% higher than that of red wines. The authors also show that each of the 19 grape varieties studied results in significantly different prices.

On the contrary, Roma et al. (2013) found red wines to be paired with higher prices compared to whites in Sicily.

The research of San Martin et al. (2008) on Argentine wines identified significant price differences between the prices of wines made from different varieties. The results showed that the Argentine producers surveyed were able to achieve prices higher than the average on the U.S. market with their Tempranillo and Chardonnay wines and some red blends, while the prices of Syrah, Bonarda and Sangiovese wines were significantly below average.

Results are summarised in Table 17.

Table 17

Summary of the literature on grape varieties determining wine prices

Author	Topic	Country	Method	Results
Kwong et al. (2017)	Factors determining wine prices in semi-parametric models	Canada	Hedonic price model	Prices for wines made from Syrah, Cabernet Franc, Cabernet Sauvignon, Merlot, Pinot Noir and Baco are significantly higher than prices for Canadian red wines made from the other varieties studied.
Ling and Lockshin (2003)	Factors determining wine prices	Australia	Hedonic price model	Prices of Shiraz and Cabernet varieties are significantly higher than prices of Chardonnay wines
Noev (2005)	The relationship between wine prices and quality	Bulgaria	Hedonic price model	White wines are more popular among consumers and also have higher prices
Ferro and Amaro (2018)	Factors explaining the price of high quality wines	USA	Hedonic price model (OLS)	White wines are significantly more expensive; grape varieties have a significant effect on wine prices
Roma et al. (2013)	Determinants of Sicilian wine prices	Italy	Hedonic price model	The prices of red wines are significantly higher than the prices of white wines
San Martín et al. (2008)	The performance of Argentine wines in the U.S. market	Argentina	Hedonic price model (2SLS)	Some red blends and Tempranillo and Chardonnay are above average, Syrah, Bonarda and Sangiovese are below average

Source: Own composition

2.7.2 Vintage year

This section examines the vintage as a labelling element.

Ashton's (2016) study on Bordeaux wines found that the impact of the vintage on wine price was typically positive for Left Bank wines and ambiguous for Right Bank ones.

Benfratello et al. (2009) also showed that a vintage of high reputation (in this case, 1997, which is “unanimously considered the best year” – Benfratello et al., 2009. p.9) was associated with significantly higher prices.

When analysing the market position of Burgundy wines in Canada, Carew and Florkowski (2010) suggested that classic vintages impact the prices positively and significantly, but on the other hand, a bad vintage resulted in significantly lower prices.

Kwong et al. (2017) were also in search for the relationship between wine prices and vintage, and by analysing Canadian red wines, they showed that prices for 2001 and 2005 vintages were 8-10% higher than for other vintages analysed.

Thrane (2009) showed that 2004 vintages were sold with a 0-11.2% price premium (depending on the model).

Table 18

Summary of the literature examining the effects of the vintage

Author	Topic	Country	Method	Results
Ashton (2016)	Comparison of expert sensory ratings	France (Bordeaux *en primeur*, red)	Hedonic price model	Fundamentally significant and positive, but very different vintage effect on price by region
Benfratello et al. (2009)	The relationship between expert sensory qualification, reputation and prices	Italy (Barolo and Barbaresco)	Standard likelihood ratio model	The reputable 1997 vintage wines are significantly more expensive than the others
Carew and Florkowski (2010)	Prices of burgundy wines	France (Burgundy)	Hedonic price model (panel)	The price of wines from "classic" vintages is significantly higher than the others
Kwong et al. (2017)	Factors determining wine prices in semi-parametric models	Canada	Hedonic price model	Canadian dry red wines have 8-10% higher prices for the 2001 and 2005 vintages than the other vintages examined
Thrane (2009)	Examination of objective and subjective factors determining the price of wines	Germany, France	Hedonic price model	The wines of the 2004 vintage are significantly more expensive

Source: Own composition

2.7.3 Individual brands

The reputation of individual brands is also an important element in the factors that affect wine prices. In general, wineries that have developed a good reputation can achieve higher prices simply by making consumers look more for their products.

Blair et al. (2017) highlighted that there is also a significant price difference between items at the same classification level that received the same expert rating (100/100 points), which was explained by individual brand value.

Di Vita et al. (2015) examined the impact of individual brands on Sicilian wines by their prevalence (proportion of consumers buying the brand among all customers in the sample). The results showed a premium that decreased along the increase of the price and even turned negative. The mark-up was + 9% for the first decile, the relationship was no longer significant for the first quartile, and was negative for the median, third quartile, and ninth decile (-3.8%; -2.4% and -5 .9% respectively), as for the average (least squares estimate; -2.4%).

Frick and Simmons's (2013) research on Mosel wines has in some cases confirmed the impact of individual brand reputation on price. Individual reputation was measured in two ways: on a seven-point scale used by the wine press, and interpreting each level as a dummy variable (then the lowest value of 1 was the reference category). Using the first approach, it was found that for a point higher individual reputation, the price was 8% higher. In the second case, only the 4th, 5th and 7th (best) levels showed a significant correlation, the price premium was 21.7%, 35.1% and 131.4%, respectively.

Examining the reputation of red wines in Bordeaux, Landon and Smith (1998) found that at the 95% confidence level, the reputations of six of the seven companies studied had a significant positive effect on wine prices and could result in a premium of up to $ 20 per bottle of wine. Here, the authors also pointed out that an increase in reputation results in higher prices than an increase in subjective quality calculated according to Parker scores. In other words, the price-increasing effect of expected quality (reputation) is significantly greater than that of real quality (Parker points).

Masset et al. (2016) examined the factors determining the price premium of Bordeaux wines sold in Hong Kong and pointed out that the price was higher if the wine already has an established reputation.

Haeger and Storchmann (2016) come to a similar conclusion when examining the prices of Pinot noir wines sold in the US, where in their view, in addition to weather, prices are mostly determined by the capabilities and reputation of the individual producer.

Roma et al. (2013), by analysing the prices of Sicilian wines and Shane et al. (2018) by examining the prices of Australian wines and found that producer reputation has a significant and positive effect on wine prices. In other words, in shops, a consumer is willing to pay more for a wine he is more familiar with, with similar content values, than for an unknown one.

A similar conclusion was reached by Viana and Rodrigues (2007) who, based on sales data for 14,000 Porto wines, showed that excellent producer reputation can increase wine prices by up to 22%.

Table 19

The relationship between wine prices and individual brands in the literature

Author	Topic	Country	Method	Results
Blair et al. (2017)	Brand value in light of expert sensory reviews	France (Médoc)	Comparison of averages	There is a significant price difference between the wines with the highest score, which can be explained by the individual brand value.
Di Vita et al. (2015)	Prices of Sicily wines	Italy (Sicily)	Hedonic price model (quantile regression)	A mark-up that decreases or even turns negative as the price increases
Frick and Simmons (2013)	Relationship between reputation and wine prices	Germany	Panel regression	The relationship between individual reputation and wine prices is significant and positive in most cases
Landon and Smith (1998)	The relationship between wine prices and quality for Bordeaux wines	France	Hedonic price model	Six of the seven producing companies have a significant positive impact on the price of their wines (+ $1-20)
Masset el al. (2016)	Characteristics of the Chinese quality wine market	China	Hedonic price model	There is a significant and positive relationship between the reputation of a wine and its price
Haeger and Storchmann (2006)	Price of Pinot noirs produced in California and Oregon	USA	Hedonic price model (OLS)	Wine prices are significantly and positively determined by individual producer abilities / reputation
Oczkowski (2001)	Hedonic wine price analysis and its methodological errors	Australia	Hedonic price model	Compared to sensory rating, reputation has a much greater impact on wine prices
Oczkowski (2016)	Factors determining the prices of Australian wines at producer level	Australia	Panel regression	Wine prices are mostly influenced by individual producer reputation, experience, producer size and co-branding
Roma et al. (2013)	Determinants of Sicilian wine prices	Italy	Hedonic price model	Producer reputation has a significantly positive effect on wine prices
San Martín et al. (2008)	The performance of Argentine wines in the U.S. market	Argentina	Hedonic price model (2SLS)	There is a significant difference between the prices for different individual brands
Shane et al. (2018)	Determinants of Australian wine prices in the UK	Australia, United Kingdom	Hedonic price model	There is a significant and positive relationship between wine prices and producer reputation
Schamel (2014)	The impact of cooperation on wine prices	Italy (South Tirol)	Hedonic price model	Cooperative wines have a higher reputation and are thus able to achieve higher prices than individual producers
Viana and Rodriguez (2007)	Factors determining the prices of Porto wines	Portugal	Hedonic price model	As the reputation of producers grows, so does the price of wines

Source: Own composition

In his 2SLS model, Oczkowski (2001) separated the effects of quality and reputation associated with individual brands on wine prices and showed that reputation has a much greater impact on wine prices in Australia than sensory rating. Similar results were obtained by the author in a later article (Oczkowski, 2016), where he examined the prices of 260 winery producers, also in Australia. According to his results, wine prices are mostly influenced by individual producer reputation, experience, producer size and co-branding.

San Martin et al. (2008) examined the role of individual brands in the U.S. market of Argentine wines, revealing a negative significant relationship in 24 of the 38 producers (the most important Argentine exporters) and a positive significant relationship in 1 case. The direction of the relationship should be interpreted in relation to the average price achieved by the producer chosen as the reference.

However, in a South Tyrolean sample of 1265 wines, Schamel (2014) found that wines produced by cooperatives have a higher reputation and thus were able to achieve higher prices than wines from individual producers. Furthermore, the results showed that if the producer organisation can achieve that individual producers increase the quality of the grapes, it will be accompanied by an increase in reputation and price.

The main findings on the relationship between wine prices and producer reputation are summarised in Table 19. Regarding producer reputation and wine prices, most of the literature has found that producer reputation has a significant and positive effect on wine prices.

2.8 Other factors

In this subchapter, I describe the factors affecting wine prices mentioned in the literature that cannot be classified in any of the categories presented above. One of these is the increasing emphasis on organic production (and certification) in recent years, but farm size, point of sale and market concentration, or even macroeconomic factors can also be decisive.

Hoang et al. (2016), for example, suggests that such other factor is the organic nature of wines. The authors examined the price premium of Japanese wines using hedonic price analysis and found that Japanese consumers paid 42.99% (8.87%) more for imported organic red (white) wines than for traditional wines, while the same price premium for Japanese organic wines was 6.44% and 1.21%, respectively.

Kwong et al. (2017) also pointed out that the prices of environmentally friendly Canadian dry red wines were 11-13% higher on average. They also showed that a 1% increase in the volume placed on the market reduces the price by about 0.11%.

Abraben et al. (2017) examined the price premium of Tuscan organic wines on the Italian and American markets between 2000 and 2008 and concluded that organically produced wines could be sold at higher prices. However, the authors also highlighted that this effect occurred differently in various quality segments and that for wines highly valued by expert ratings, this premium is already negligible.

Niklas et al. (2017) examined the standard deviation of fair trade wine prices in the UK between 2007 and 2012 and found that the standard deviation of fair trade wine prices was lower than that of other wines.

Jiao (2017) analysed several different macroeconomic variables between 1996 and 2015, which affected wine prices. Results suggested that the demand growth of developing countries and the depreciation of the US dollar significantly increased prices of high-quality Bordeaux wines. The author also showed that the slowdown in economic growth in developing countries since 2011 and the devaluation of national currencies have had a negative impact on the French luxury wine market. The author also demonstrates in his article that money supply, real interest rates, and increases in investment funds have all had an impact on quality wine prices. Overall, Jiao (2017) demonstrated a significant positive relationship between wine prices and economic cycles.

As to other determinants, Ling and Lockshin (2003) analysed winery sizes as potential determinants of wine prices and suggested that prices of small and medium wineries were generally higher than that of large wineries.

Masset et al. (2016), however, also draws attention to the fact that the place of sale also matters in the price of a wine. Their analysis examined the factors determining the price premium for Bordeaux wines and pointed out that auctions in Hong Kong typically achieve higher prices for high-quality French wines than other auctions.

Michis and Markidou (2013) examined the determinants of Cypriot retail wine prices and pointed out as a new dimension that, in addition to the above factors, wine prices are more determined by market concentration than price competition between competitors.

Table 20

Summary of the literature on other factors determining wine prices

Author	Topic	Country	Method	Results
Hoang et al. (2016)	Price premium for organic wines	Japan	Hedonic price model	The price premium of imported organic wines is higher than that of domestic organic wines and traditional wines
Kwong et al. (2017)	Factors determining wine prices in semi-parametric models	Canada	Hedonic price model	Prices for environmentally friendly Canadian dry red wines are 11-13% higher on average. A 1% increase in volume reduces the price by 0.11%.
Abraben et al. (2017)	Relationship between wine prices and organic production	Italy	Hedonic price model	In the Italian and American markets, organically produced Tuscan wines can be sold at higher prices
Niklas et al. (2017)	Price dispersion of fairtrade wines	United Kingdom	Hedonic price model	The prices of fairtrade wines show a lower variance than the prices of traditional wines
Jiao (2017)	Macro factors influencing wine prices	France	Time series regression	There is a close relationship between wine prices and macro factors
Ling and Lockshin (2003)	Factors determining wine prices	Australia	Hedonic price model	The prices of the products of small and medium-sized wineries are higher than the prices of wine of large wineries
Masset et al. (2016)	Characteristics of the Chinese quality wine market	China	Hedonic price model	Auctions in Hong Kong typically offer higher prices for French quality wines than other auctions
Michis and Markidou (2013)	Examination of Cypriot retail wine prices	Cyprus	Panel regression	In addition to the above factors, market prices are more determined by market concentration than price competition between competitors.
San Martín et al. (2008)	The performance of Argentine wines in the U.S. market	Argentina	Hedonic price model (2SLS)	The quantity placed on the market is inversely proportional to the price

Source: Own composition

San Martin et al. (2008) examined the market share of Argentine wines in the United States and found that the volume placed on the market and the price are inversely proportional, with each additional carton of wine (12 bottles) reducing the price by 0.0005% (or 4.2% decrease per 1,000 bottles).

The main dimensions of the relationship between other factors and wine prices are illustrated in Table 20.

2.9 Critical analysis of the literature

In the previous chapter, I summarised the results of literature describing the factors affecting wine prices. In order to better separate the information in the articles as well as my own thoughts on this, a critical analysis of the literature will be given in a separate chapter. The aim of this is to systematically present the thoughts that arise in relation to what is read, which is of great relevance in the planning of my own research. In the course of this analysis, I try to address both substantive and methodological issues, first in general and then in terms of the aspects examined by the 46 articles presented. The conclusions set out here contribute greatly to the better theoretical foundation of my own research.

2.9.1 General methodological aspects

About 70% of the work described in the previous chapter uses hedonic price analysis. Models based on this methodology explain the price of products with variables describing their intrinsic properties (Rosen, 1974), that is, we consider goods as a set of descriptive characteristics (this methodology was first used to analyse the market for durable consumer goods, primarily cars). Accordingly, the observed price differences reflect the differences between the sets of characteristics corresponding to each product. This idea applies on the condition that the market is perfectly competitive.

Unwin (1999) made a very serious methodological critique of hedonic price analysis examining the wine market. In his view, Rosen's (1974) condition of perfect competition does not always stand, the explanatory variables included are not independent of each other and the consumer's thoughts on wine quality are not scientifically explored enough to draw valid conclusions about price-quality from regression calculations. Unwin also criticises the practice of choosing explanatory variables; according to his wording, researchers performing hedonic price analysis rely primarily on data already available rather than seeking the optimal solution. Another problem is that the selected explanatory variables are in many cases not independent of each other, therefore the significance levels are not real either. This is particularly the case for variables describing expert ratings, which raise additional inaccuracies and subjectivity. Accordingly, the explanatory variables associated with expert ratings are highly dependent on the characteristics of the experts who produce them (prior training, experience, etc.).

Nevertheless, from a demand-side point of view, the relevance of the most common variables included in hedonic price analyses is not certain as consumers do not know them. Furthermore, Unwin considers the goal of these analyses uncertain as scientific theory on consumer appreciation of wine quality is insufficient. He suggests hedonic price indices take the information available on the label (origin, varietal, producer, vintage year, the actual content in alcohol) into account as they are available in the moment of purchase. Instead of further detailing hedonic price indices, Unwin suggests putting more emphasis on assessing consumer attitude using qualitative methods.

In response to the above criticisms, Thrane (2004) provides theoretical and practical guidance for the proper design and execution of hedonic price analyses. He argues that the users of this methodology start from existing data for pragmatic reasons (the ideal variable structure would require a much larger number of elements than usual). In his view, some of Unwin's criticisms stem from the choice of inappropriate econometric methodology.

Thrane acknowledges that hedonic price analyses are not undistorted if Rosen's condition for perfect competition is not met (since consumer preferences also influence the price), but he considers this problem meaningless if the results are appropriately interpreted. Hedonic price analyses are not intended to measure consumer behaviour but are essentially supply-oriented; that is, they examine the relationship between specific characteristics of the supply side and prices. In his view, the criticisms of the econometric solutions used by the researchers cited by Unwin are valid. However, instead of completely abandoning hedonic price analysis as a wine economics methodology, he suggests the right (supply-side) interpretation of the results and the competent application of available econometric tools (e.g. two-stage analysis, management of multicollinearity).

Thrane (2004, p.133) positively formulates research questions, too, that he considers the hedonic price analysis as a useful methodology to answer:

- "How much does the consumer have to pay extra or less for a wine from district X as opposed to a wine form district Y or the average wine?"
- "How does the wines' vintage affect their price?"
- "How are the subjective qualities of wines associated with their price?"

A review of the literature presented before also confirms the validity of these criticisms. I believe that data-driven model specification is mainly due to the scarcity of expert ratings, as a large part of the articles rely on the databases of various wine magazines, wine journals (primarily *Wine Spectator*) or various well-known wine critics (primarily *Robert Parker*). This reduces the scope of the studies to the focus regions of these press products or experts. Accordingly, Bordeaux wines or products, regions and countries with a strong presence on the on the US market are the focus of the literature. In several respects, the situation is somewhat easier when examining markets where the commerce flows through a monopoly trader (e.g. Carew and Florkowski, 2010).

2.9.2 A better understanding of geographical indications

The predominant role of geographical indications is confirmed by the fact that 25 of the 46 articles examined were related to some extent their relationship with wine prices. Most of these literatures also highlighted that there are very significant, statistically significant differences between the effects of specific geographical indications on wine prices, the reasons for which merit further investigation. In other words, it is not the mere fact that a product bears a geographical indication that has value, but the specific geographical indication.

Government measures in wine producing countries regulating the practice of labelling the origin have been introduced since the beginning of the 20th century – yet, regional regulations on the delimitation of the area were applied much earlier in Tokaj, Burgundy, Champagne, Chianti or Porto. Meloni and Swinnen (2018) identified two common elements in the protection and geographical delimitation of the first GIs: (1) changes in wine trade causing conflicts between historical and potential new producers, and (2) the (excellent) link between the historical producers and the political regime. Geographical indications play an important role in European Union agriculture and are key in the wine sector. Despite the uniformity of the EU regulatory framework, we can distinguish two essential approaches to geographical indications: the Germanic system and the Latin system. In short, the Germanic system focuses on the ripeness (and thus the quality level, or the technological quality according to Botos and Szabó, 2002) of the grapes, while the Latin system on the typical products of their origin (or on the classification quality according to Botos and Szabó, 2002 – the French concept, underlying the Latin system, is perfectly summarised in Braham, 2003).

The legal protection of geographical indications is covered by intellectual property rights measures and there are currently four different regimes under European Union law (wine products, agricultural products and foodstuffs, aromatised wines and spirits). For wine products, EU law distinguishes between two types of geographical indication: protected designations of origin and protected geographical indications. The difference between the two is not the degree of legal protection, but the nature of the relationship between the product and the place of production: the former is close, and the latter is loose[5]. The most important element of the regulation is that the exact conditions for the use of the geographical indication are determined by the competent producer communities in a so-called in the product specification. This document shall contain the requirements for the delimitation of the place of production of the grapes, the quality parameters of the raw material of the grapes, the oenological practices, the chemical composition and the organoleptic characteristics and the proof of the link between the product and the place of production.

Geographical indications are of dual nature: they can be interpreted as factors decreasing information asymmetry, hence increasing efficiency, or seen as rents for those who own the production factors (Meloni and Swinnen, 2018). For a better understanding, we need to review primarily their qualities that stem from their collective nature. GIs embody a collective reputation, which in Tirole's (1996) approach can be understood as the totality of the individual reputation of the individuals who make up the group. Individual and group reputation are interdependent and depend on past performance (the quality of the product) in this approach. Thus, the stronger the incentives are to maintain (improve) individual reputation, the better group reputation will be. In this area, due to the collective nature of GIs, incentives in the opposite direction emerge within the group. On the one hand, with the increase of the size of the producer community, the likelihood of free-riding increases (Winfree and McCluskey, 2005), and on the other hand, joint branding allows for quality improvement and investment in quality where it would not otherwise occur (Fishman et al., 2018). As a consequence of collective nature, wineries using a geographical indication are, on the one hand, interdependent and, on the other hand,

[5] Regulation (EU) No 1308/2013 of the European Parliament and of the Council of 17 December 2013 establishing a common organization of agricultural markets and amending Directives 922/72 / EEC, 234/79 / EC, 1037/2001 and 1234 Article 93 (a) and (b) of Council Regulation (EC).

competitors of each other, seeking to differentiate themselves from other members of the group by using their individual brands (Patchell, 2008). Therefore, given the limited demand for products bearing a given geographical indication, the reputation of the group is also exploited to the detriment of each other (Castriota and Delmastro, 2012).

The reputation of geographical indications can thus be interpreted as a common pool resource in the crossfire of conflicts between short-term individual and long-term group interests, like the commons in the famous example that illustrates this situation (Hardin, 1968) as they fulfil the criteria in terms of both impossibility of exclusion and competing consumption (congestion – Mike and Medgyesi, 2016). Ostrom (2003) proposes common governance as a solution of these problems. In this case, the group members determine the conditions of access and use of the common pool resource. This is the same approach that the European Union’s new regulatory framework (Reg. No. (EU) 1308/2013) on geographical indications applies.

Using a GI imposes additional costs due to the additional regulations. Therefore, producer communities need to find the ideal balance when designing regulation; they must avoid both excessive rigours with high costs and the loss of meaningful differentiation as a result of excessive leniency (Tregear and Gorton, 2005). Maintaining the credibility of a GI representing collective reputation can pragmatically be assured by the sensory and analytical testing of the end product (Winfree and McCluskey, 2005, and Tregear et al., 2007).

Nevertheless, the collective reputation in a competitive environment is not a perfect guarantee of quality. Moreover, reputation building is mainly a cost-effective solution in cases where the product in question is produced at a high cost, or the membership of the producer community is relatively homogeneous, and the marginal cost is decreasing (Shapiro, 1982). The distinctiveness and identifiability that comes with of the use of geographical indications are particularly falling in those medium and lower price categories, where consumers find it easier to understand the New Wine World’s grape variety-based labelling practices (Tregear and Gorton, 2005). However, as indicators of unique quality, geographical indications may allow a higher price to be achieved, which may prove essential in competing with more efficient New Wine World countries (Tóth and Gál, 2014). It is perhaps not by coincidence that France and Italy are able to achieve price discrimination in certain non-European wine export markets (Balogh, 2017) – these two countries possess 60% of European wine GIs (European Commission, 2019).

Even partial consumer information and the setting of quality standards (both in terms of character and quality level) can lead to welfare gains – the optimal level (i.e. extra costs) of investing in quality shall be determined accordingly in local rules. The real value of specific geographical indications is also influenced by the socio-economic characteristics of the producer community. Well-organized and managed producer communities can act more effectively for the collective benefit of their membership (Carter, 2015).

It follows directly from the above that each geographical indication (as the presenter of the place of origin on the label) has a unique relationship with wine prices. Therefore, on the one hand, their impact must be assessed individually, and on the other hand, it is worth exploring the factors behind the very different effects.

2.9.3. The inclusion of expert ratings (scores)

A number of other literature articles argue, in addition to the critical remarks previously made by Unwin (1999), that specialist sensory ratings, and in particular scores for measuring quality levels, should be taken with care.

Expert ratings can address both dimensions of wine quality. Judgement and description of the character are in most cases done verbally, perhaps by determining the intensity of each factor, while the quality level is usually evaluated on a scale.

Several authors question the role of wine experts, and even more so the validity of their expert ratings. Many of them have doubts about the capabilities of wine experts; Hodgson (2009) points out that only 30% of the observed critics can be considered real experts. Ashton (2012) compared expert judgment in six other disciplines (medicine, clinical psychology, business, auditing, HR, meteorology) to examine the reliability and level of consensus of expert panel decisions. In all cases, the reliability was higher than the consensus, but both were significantly lower for the wine evaluation. Thus, there is little evidence that experienced wine reviewers can be considered professional.

The extent to which consumers can understand expert opinions is questionable. Focus group experiments (Veale and Quester, 2008) have shown that even the most sophisticated wine consumers do not know the organoleptic qualities of wines with certainty. Even those consumers cannot pair expert wine descriptions with the proper wines who otherwise successfully distinguish between two wines (Weil, 2007). Moreover, unskilled wine consumers value cheaper wines (Goldstein et al. 2008). At the same time, the quality surplus represented by more expensive wines is typically appreciated by better-educated wine consumers.

As described in Subchapter 2.5, the literature, in spite of these doubts, put great emphasis on exploring the impact of expert ratings on prices. From a total of 46 articles, 25 articles address this topic.

In the vast majority of cases, the literature examines the impact of expert ratings of quality level on prices, yet, there are exceptions. It is quite typical that none of the articles in the literature applies the OIV's (2009) system. In contrast, the scoring systems used by the Anglo-Saxon wine press are widespread: the American lawyer, Robert Parker's (Wine Advocate) 100 point system, the Wine Spectator 100 point system or the British wine journalist, Jancis Robinson's 20 point system (Ashton [2016] provides an excellent comparative analysis of Parker and Robinson's system).

It is quite apparent to associate the expert ratings of wines with prices, but this procedure has several pitfalls, which, unfortunately, are not mentioned in most of the cited works.

The first such trap is the measurement level of scales designed to measure the quality level. The authors of the papers in question, implicitly, consider the scores to be variables on a ratio scale, whereas a brief analysis of the scoring systems provides evidence to the contrary. In fact, none of the scales mentioned before has as many grades as claimed: the OIV's 100-point scale is actually of 61 points (40-100 points), the Parker scale is of 51 (50-100 points), as is the Wine Spectator's[6], and Robinson's scale is of 9 grades (12 to 20 points). Thus, their treatment as a ratio scale would be possible only after a transformation similar to that used in converting the temperature value expressed in °C to Kelvin. However, this could only be carried out if these scoring systems were interval scales. Unfortunately, however, with the possible

[6] Robinson (2019) claims that Wine Spectator also uses Parker's system ("Wine Spectator adopted Parker's system"), but a detailed comparison of Wine Spectator's (2008) information and Parker's scale (Ashton, 2016 p.267) reveals that there are so many minor differences between the two systems that they can no longer be considered the same.

exception of the OIV's system, there are serious concerns about this assumption: minimal information is available on the exact structure and application of these scales, meaning that in practice, for example, is the difference between wines of 82 and 83 Parker points the same as between wines of 99 and 100 Parker points. Therefore, a reasonably accurate and careful researcher considers these scores as variables on an ordinal scale (and may make exceptions only with the OIV's system).

A further problem with these scales is that results obtained at different times and with different experts are not necessarily consistent. An organoleptic description or scoring of a quality level is in any case strictly a snapshot of the wines examined, even if it includes expectations for the future. Therefore, when examining the relationship between price and expert organoleptic judgment, the same date data should always be considered. The problem of inconsistency in expert organoleptic ratings is more pronounced when the sample on which the cross-sectional analysis is conducted contains data from a very long period (for example, more than a decade) as there is no guarantee that the taste perception of the reviewing experts is constant over that period, it would have been calibrated in the same way, or even the composition of the expert panel remained the same. However, in order to defend research based on such data, it should be noted that the press products concerned are likely to do so in their well-conceived interest.

The second trap (see Section 2.9.1.) is the simple incorporation of expert ratings into models explaining price with several independent variables. That poses a severe endogeneity problem (Oczkowski, 2001) as expert ratings reflecting the quality level of wine are obviously not independent of the factors impacting (origin, variety, harvest year) or describing (analytical data) wine quality. Thus, the statistical significance of the explanatory variables may be severely distorted. This problem is simply ignored by a large part of literature reviewed, while others (Combris et al., 2000) use triangulation (comparing the results of models with and without expert ratings) or a two-stage least squares model (San Martín et al., 2008 and Thrane, 2009).

2.9.4. Chemical composition

Of the articles presented in this chapter, five deal with the relationship between the chemical composition of wine or at least one of its components and price. Each of these models involves alcohol content, three articles take only this into account, and two other papers considers the sugar content, volatile acidity, total acidity, concentration of sulphites, and the ratio of free and bound sulphites.

The articles do not always detail the source of the data; however, I highly assume that the source for alcohol content is its mandatory labelling. It is beneficial on the one hand, as the consumer sees precisely what they are buying, and on the other hand, one shall understand that this data is distorted – both in the European Union and the US market.

In Europe, the actual alcoholic strength may only be labelled at a rate of 0.5% vol, and a tolerance of 0.5%vol (see Article 44 of Regulation (EU) No 2019/33), i.e. an actual alcoholic strength of 12.3% vol shall be indicated as 12.0 %vol or 12.5% vol.

The situation is more complicated in the United States, as this element can be labelled with a tolerance of 1.5% up to an actual alcoholic strength of 14% vol (TTB, 2018) and above this threshold, the tolerance is 1% vol. In practice, this means that the cited wine of 12.3 %vol may be labelled with an alcohol content of 10.8%-13.8 vol, which is quite a large interval.

3 METHODOLOGY AND DATA USED

3.1 Research questions

The main aim of this research – as described in the introduction – is to reveal the factors influencing wine prices in the Hungarian market, or other words; which factors explain the differences between wine prices. In this context, the endeavour is to include all the factors described in the literature review.

The second step of the research intends to explore in detail the role of geographical indications.

Accordingly, my main research questions are:

MAIN QUESTION 1: What factors explain the differences in wine prices in the Hungarian wine market?

MAIN QUESTION 2: What internal and external factors explain the market value of Hungarian GIs in the Hungarian wine market?

3.2 Hypothesises

Given the findings of previous studies, the following hypothesises were developed.

3.2.1 First step

H1.1 Certain geographical indications have a positive impact on the price.

This hypothesis lies on the assumption that *theoretically*, a geographical indication possesses certain added value on the market. This added value ensures that the producers use it despite the additional costs involved. In contrast, I expect some geographical indications not to have significant added value.

I assume this hypothesis does not stand up to scrutiny for any geographical indication. As literature showed, GIs are expected to have a positive price premium under certain conditions regarding the producer group (Carter, 2015), the interconnection of individual and group reputation (Patchell, 2008 or Castriota and Delmastro, 2012), the motivation for investing in quality (Fishman et al., 2018), consumer legibility (Tregear and Gorton, 2005). Each observed GI would get its own dummy variable, as the reference group would be the wines without geographical indication (so, in theory, the possibility of negative price premium exists).

Therefore, when examining this relationship, it is expedient to examine the impact of each GI one by one instead of grouping them.

Furthermore, the impact of labelling crus (parcels) should be assessed by adding a common dummy to the model for single vineyard wines.

H1.2 Good individual brands have a positive price premium.

Although individual brands are not the most important element for the Hungarian consumers, (Szolnoki and Totth, 2019), it is assumed that individual brands serve as an important factor in achieving price premium for wines. Hungarian producers often do not use consciously geographical indications and attribute far greater importance to the individual brands (which are usually the most prominent element on wine labels).

H1.3 The concentration of compounds would be positively linked to prices.

According to an alternative formulation of this hypothesis, in general, the more concentrated (or, the less diluted) a wine is, the higher its price may be. An evident cost reason supports this hypothesis: the production of more concentrated wines costs more. The question is whether this is present in the price or not.

H1.4 The age of the wine is positively related to the price.

I assume that the price of more mature wines is higher than that of younger Ones. The higher cost of production justifies this, but the consumers' belief that wines will only get better and better over time may have a more serious impact, too.

H1.5 The quantity (lot size) negatively impacts the price.

Obviously, the less the available quantity is, the more the price will be (because of various reasons such as lower selling pressure, higher average cost). From another point of view, the assumption is that wine makers are better off producing and selling higher priced wines in a smaller quantity (for reasons of quality control capacities etc.).

H1.6 Wines of fashionable varietals or the colour red cost more.

Colour and varietal names are commonly used for the differentiation, the explanation or the marketing of wines. Therefore, I assume that wines of fashionable varietals (e.g. international red varieties) and colours (red) tend to cost more than other wines.

Furthermore, it would seem plausible to examine the impact of expert sensory ratings on price, but for several reasons, I disregard it. On the one hand, as explained in section 2.9.3, there are several major methodological concerns about this approach, either considering the statistical characteristics of the different scoring systems or the endogeneity that threatens the validity of the models studied. However, these theoretical problems alone could be addressed by appropriate choice of methodology (e.g. OIV organoleptic scoring system, use of models dealing with endogeneity). However; expert ratings about all elements of a sample with a size required for the models presented in the next section cannot be obtained from external sources (as there is simply no such), and the organisation of tastings for only this purpose would clearly exceed the scope of this research.

3.2.2 Second step

Given their policy relevance, the second step aims to reveal the factors influencing the performance of geographical indications on the market.

H2.1 The market value of a GI linked to a homogenous producer community is high.

The more homogenous the group of producers is, the easier the collective action is; hence, higher prices and revenues can be reached. As geographical indications are of a collective nature, their management requires high quality collective action. Group homogeneity is an important issue of collective action (Carter, 2015; Evans and Guinnane, 2007, Olson, 1965).

H2.2 The stricter the rules of using a GI, the higher its market value will be.

GIs, by theory and the assumption of the lawmaker, signal distinctive product quality. Thus, the wine quality (e.g. quality standards or rules on organoleptic characteristics) set in the product specification shall be easily and meaningfully differentiated. The stricter (the more defined) are the rules on the use of a GI, the more specific the quality of the wines bearing it will be. It is clear from the theoretical background described above that the use of GIs, in this case, reduces information asymmetry much more, and the smaller the information asymmetry, the more likely it is that a quality surplus will be realised at the price of the product.

H2.3 The higher the barriers to entry are, the higher the market value is.

Barriers to entry hinder new competitors to enter the market and contribute to higher prices by lowering the amount of supply and the level of competition. In case of geographical indications, the most effective barrier is the delimitation of the production area. Determining such an area is theoretically based on viti-vinicultural factors such as (micro-)climate or soil. However, from an economic point of view, it serves as an effective entry barrier as a newcomer may not use the geographical name for products originating or produced outside the delimited area.

H2.4 The better the geographic area of a GI is, the higher the market value will be.

As place of origin is an important factor of wine quality, it is obvious that the better the delimited area is, the higher the quality level will be, which is assumed to impact the market value.

3.3 Operationalisation and source of data

3.3.1 First step

In the first phase of the research, the observation unit is the specific batch of wine, so each of the variables used in this phase represents information about actual wines.

The dependent variable is the price of a particular batch of wine. Due to different cost structures and customer reaches, there may even be significant differences in prices for the same wine item across different sales channels. Thus, the primary consideration is to identify the relevant market segment, sales channel accurately. In order to equalise price differences due to the different volume of the packaging (as in Ugochukwu et al., 2017), all prices were expressed in HUF/0.75 litre.

The explanatory variables were chosen according to the hypotheses described above:

H1.1 Geographical indication (dummy variables). Each geographical indication of a wine batch in the sample is represented by a dummy variable whose value is 1 if the batch in question bears the geographical indication concerned, otherwise 0. In the case of wines without a geographical indication, the value of all geographical indications dummy is 0, of course.

At the same time, I take into account the indication of vineyard names (crus), by using a single-vineyard name dummy, which is set to 1 if the name of the wine bears the name of a vineyard, otherwise 0.

The data source is the geographical indication on the label of the wine observed. In all cases, I check the lawful use of this in the public database of the wine authority.

H1.2 Individual brand (dummy variables). Information on the producer of a wine.

Given the large number of possible brands, they are grouped according to their performance on the two most important prizes that winemakers may receive in Hungary: “The Winemaker of the Year” and “Winemaker of the winemakers”

I believe that there are several reasons why these two charges should be taken into account. On the one hand, both the candidates and the winners of these awards are defined by professionals and experts, so it can be assumed that those involved have achieved a high level of professional performance in the past. On the other hand, both awards have traditionally received considerable media attention, as both the nominees and the winner are a defining element of the public discourse on wines at the time of the year. This assumes that the individual brands concerned have a credible and positive reputation with the consumer.

Therefore, I group the producers into three tiers. The first tier (dummy) consists of producers who have received either of the two awards, and the second tier (dummy) contains those that were nominated and the information on the nomination is available for consumers. The rest of producers form the reference group.

Information on the winners and the nominees is provided by the web sites of these prizes.

H1.3 The concentration of compounds would be positively linked to prices.

According to article 24/A. of law No. XVIII of 2004 on grape-growing and wine management of Hungary, wine products may only be marketed or shipped out of the country with a permit issued by the wine authority. This permit is granted following the measure of 12 chemical compounds and an organoleptic test.

When examining this hypothesis, I take into account the sugar-free extract content (g/l) and the residual sugar content (g/l). Actual alcohol content and acidity (or pH) are still important compounds, but I omit them in the models to avoid multicollinearity. The role of sugar is examined by colour, as I assume that the relationship between sugar content and price is different for white and other (rosé, red) wines (as all great natural sweet wines are white).

Data on the chemical composition and the colour are found in the marketing permit issued by the wine authority.

H1.4 The age of wine is positively related to the price.

The age of the wine is the difference between the date (year) of data collection and the date (year) of the harvest of the grapes used as the raw material. For items where this information is not available (or which are from multiple vintages), the year of the last harvest period before marketing is considered the vintage year.

H1.5 The quantity (lot size) impacts the price in a negative way.

The marketing permit contains the data on the quantity (expressed in litres). Data were provided by the wine authority.

H1.6 Wines of fashionable varietals or the colour red cost more

The colour and the grape variety can be presented by dummy variables in the models. As the number of potential combinations of grape varieties is high, eight groups were created:

1. white - variety not declared
2. white - other variety
3. white - Cserszegi or Irsai
4. white - other aromatic variety

5. rosé
6. red - Bordeaux varieties
7. red - other varieteies
8. red - variety not declared

Rosés were used as a reference category; therefore, the models would include seven different dummies describing colour and varietal.

Data on the varietal composition and the colour are found in the marketing permit issued by the wine authority.

3.3.2 Second step

The second step of the research aims to reveal the factors influencing the market value of GIs.

Market value can be operationalised in different ways; therefore, several models are specified in the second step. The first group of models include the natural logarithm of the average price of each GI, while the second and third group uses the price premia of the GIs that were estimated in the first step.

H2.1 The market value of a GI linked to a homogenous producer community is high.

The homogeneity (or heterogeneity) of the local producer community is primarily interpreted in terms of how similar or different their expectations may be concerning an actual GI. I treat this as a function of the differences in the extent of the use of a particular GI. This is measured as group heterogeneity by the standard deviation of the total amount of wines marketed by a single producer with the geographical indication concerned. The lesser the standard deviation is, the more homogenous is the producer community considered.

Data were provided by HNT (wine product certificate of origin type “C”).

H2.2 The stricter the rules of using a GI, the higher the prices will be

Although wine quality is multidimensional, as the measurement of character is quite hard, only information on quality level is considered: the maximal yield of the grapes set out in the product specification (expressed in hectolitres of new wine per hectare). Generally, the higher the yield, the lower the quality level (thus, the relationship is negative). The maximal level of yield is defined in the product specification of each GI and is expressed in hectolitres of new wines per hectare.

The observation considered the wine year preceding the collection of data on prices. Quality regulations were observed in the product specifications of the GIs (see AM, 2019).

H2.3 The higher the barriers to entry are, the higher the market value is

This factor is measured as the percentage of the area covered by vineyards (of authorised varietals) compared to the whole size of the delimited area (the size of the area included in the categories of wine grape cadastre defined in the product specification). The higher this percentage is, the harder is to enter the market for new competitors (either with the intention of planting vines or buying grapes), therefore the higher should be the prices.

The observation considered the wine year preceding the collection of data on prices. Data on area size were provided by National Land Centre (size of the delimited area), HNT (area of vineyards by grape varietals) and retrieved from the product specification (authorised grape varietals, delimitation of the area).

H2.4 The better the geographic area is, the higher the market value will be

Quality of the land (from a viti-vinicultural point of view) is measured by a 400-point system (cadastral points). Data were provided by the National Land Centre.

3.4 The model

3.4.1 First step

In the first step of the study, several hedonic price indices are specified (as it is applied in the literature presented), which may be described as follows:

$$\ln P = \beta_0 + \beta_i * GI_i + \beta_1 * SV + \beta_j * IB_j + \beta_2 * SFE + \beta_3 * SUGAR * WHITE + \beta_4 * SUGAR * NONWHITE + \beta_5 * AGE + \beta_6 * \ln Q + \beta_k * CW_k + \varepsilon$$

where:

P: price

GI_i: GI dummies,

SV: dummy for single-vineyard wines,

IB_j: individual brand dummies,

SFE: concentration of sugar-free extract,

SUGAR: sugar content,

WHITE: white wine dummy,

NONWHITE: dummy for rosé or red wines,

AGE: age of the wine,

Q: lot size,

CW_k: colour and varietal dummies.

Two factors justify the application of several models. First, certain geographical indications are segmented into two or three quality levels using additional terms to the name itself (e.g. Eger Superior or Villány Prémium). To deal with this phenomenon, two different approaches were applied: (A) these geographical indications were treated as one single name or (B) two or three separate names (depending on the actual number of quality levels). Moreover, as heteroskedasticity occurred, (1) robust standard error models were used instead of ordinary least squares models (White, 1980). Furthermore, (2) quantile regressions were also run (for the first decile, the first quartile, median, the third quartile and the ninth decile).

The main difference between OLS and quantile regression is the estimation method. While in OLS, the coefficients are estimated by minimising the squared sum of the differences, while in the quantile regression, the asymmetrically weighted sum of the absolute differences is minimised. The advantage of quantile regression over OLS is that it is applicable to examine the relationship between arbitrary quantiles, not just the means (Hajdu and Hajdu, 2013). Therefore, on the one hand, the method is not sensitive to extremes and, on the other hand, it gives a complete picture of the nature of the relationships. Moreover, using quantile regression models contribute to tackle heteroskedasticity (as suggested by Di Vita et al, 2015) that occurs often in hedonic price indices.

When designing the models, I consider the bottom-up principle proposed by Thrane (2004), that is, I proceed to integrate groups of explanatory variables according to hypotheses H1.1-H1.6. Thus, when examining and interpreting the results, not only the indicator of explanatory value (adjusted-R^2) or model selection indicators (e.g.

AIC, BIC), but also the change in the estimated coefficients of the explanatory variables may be observed.

As mentioned above, during the first phase four different model groups (A1-A6; B1-B6) will be constructed, as illustrated in Table 21. All models were estimated using STATA software.

Table 21

Models of the first step

		treatment of GIs with several quality levels	
		A – as a sole GI	**B – as multiple GIs**
model specification	**1 – OLS (or robust standard errors)**	A1	B1
	2 – quantile regression (first decile)	A2	B2
	3 – quantile regression (first quartile)	A3	B3
	4 – quantile regression (median)	A4	B4
	5 – quantile regression (third quartile)	A5	B5
	6 – quantile regression (ninth decile)	A6	B6

Source: Own composition

3.4.1.1 An alternative approach[7]

In order to provide an alternative approach of the analysis of determinants of wine prices, Partial Least Squares (PLS), a relatively new methodology for estimating Latent Variable Path Models (LVPLS) was used. From a broader conceptual perspective, LVPLS is a statistical data analysis methodology for studying a set of blocks of observed variables which can be summarised by latent variables (Outer model) and the linear relationships between the latent variables (Inner model). Establishing the relationships requires some previous knowledge. The main principles of PLS technique for principal component analysis were described by Wold (1966), and the first PLS analytical tool for blocks of variables was developed in 1975 (Wold, 1975). The whole algorithm was published in the 1980s (Wold, 1982 and 1985).

[7] Here, I would like to thank Sándor Kovács for his contribution to the preparation of this point and section 4.1.8

Further developments were made by Lohmöller (1989) and developments regarding the applications to SEM problems and path models were given by Chin (1998) and Tenenhaus et al. (2005).

PLS is rather an explanatory technique with a component-based (variance-based) procedure and allows working with small sample sizes and makes less strict assumptions about the distribution of the data (compared to structural equitation modelling – Chin and Newsted 1999). PLS has the capacity to deal with very complex models including a high number of latent variables (LV), manifest variables (MV), and relationships (Garthwaite 1994; Barclay et al. 1995). In PLS, the relationship between an LV and its MVs can be modelled as either formative or reflective way.

As the major disadvantage of PLS, there is no global criterion to optimise that would allow the evaluation the overall model. However, Amato et al. (2004) propose a global criterion of goodness-of-fit (GoF).

In order to estimate the causal relations between prices, GIs, individual brands, chemical composition, quantity, colour and varietal composition, a Latent Variable Path Analysis with Partial Least Squares (LVPLS) with a reflective method for index construction (Diamantopoulos, 1999) was applied, using XLSTAT software.

The variable structure was changed for these models as the model design includes nine latent variables for four different dimensions of the study. Regional origin is represented by five variables, one for each wine region (regional origins), while other latent variables are individual brand, colour and varietal, composition and market situation. Considering the extreme levels of sugar content and high prices, all wines from the Tokaj region were excluded as they would majorly distort the results.

The manifest variables of *regional origins* are geographical indications are the GI dummies whose value is 1 if the batch in question bears the geographical indication concerned, otherwise 0. Here, approach B is applied for GIs segmented into two or three quality levels (so they are treated as separate names). Two additional dummy variables were generated: one for wines without a GI and another for wines with not Hungarian protected geographical indications (PGIs) that were imported in bulk by wineries operating in Duna region and then released to the market under their own brands (imported PGI).

Individual brand reputation is measured by three dummy variables: Tier1 and Tier2 are supplemented by Tier3, which contains the rest.

Chemical *composition* of the wines is measured by four MVs: sugar-free extract content (g/l), residual sugar content (g/l), pH and actual alcoholic strength (by volume).

The LV *colour and varietal* is manifested by eight dummy variables (white - variety not declared, white - international variety, white - aromatic variety, white - other variety, rosé, red - Bordeaux varieties, red - other varieteies, red - variety not declared).

Finally, the manifest variables of *market situation* are price (HUF/0.75 litres) and quantity (litres).

3.4.2 Second step

As the number of GIs observed is obviously limited, the methodologic room for manoeuvre is majorly restricted in the second step. Even multiple OLS regression analysis including all variables would face substantial methodological obstacles, as the thumb rule suggests including 10-20 observations per estimated parameter (Harrel [2015 p.72-73] describes 15 observations per parameter as "a good average requirement").

Therefore, the study shall use simple solutions, even the scope of multivariate regression is limited, and the application of more sophisticated methods aimed to reveal the interconnection of variables (e.g. 2SLS regression or structural equitation models) is virtually impossible[8].

First, restricted models are estimated to test each hypothesis separately. Then, as group heterogeneity and yield are not assumed to be independent of each other, extended models including yield, barriers to entry and the quality of the geographic area are estimated:

$$MV = \beta_0 + \beta_1 * YIELD + \beta_2 * BE + \beta_3 * LANDQUAL + \varepsilon$$

where:

MV: market value of the GI, measured by the ln of mean price or the estimated

YIELD: maximal yield for using the GI

[8] These models were applied and showed promising results at first glance; however, the results of post estimation statistics showed poor model fit.

BE: barrier to entry, the percentage of the area covered by authorised varietals compared to the whole size of the delimited area
LANDQUAL: land quality, average cadastral points of the delimited area

Following the different approaches of the first step, six different models will be constructed (models C1-D3)., as described in detail in Table 22.

Table 22

Models of the second step

		Treatment of GIs with several quality levels	
		C – as a sole GI	**D – as multiple GIs**
Operationalisation of market value	**1 – mean price *(log)***	C1	D1
	2 – estimated implicit price (model A1/B1 – robust standard errors regression)	C2	D2
	3 – estimated implicit price (model A4/B4 – quantile regression for the median)	C3	D3

Source: Own composition

Furthermore, to test their connection, yield is regressed by group heterogeneity.

$$YIELD = \gamma_0 + \gamma_1 * GROUP + \varepsilon$$

where:
YIELD: maximal yield for using the GI
GROUP: producers' group heterogeneity

3.5 The sample

3.5.1 Theoretical considerations regarding sampling

Before presenting the sample, it is worth to evaluate the sampling procedures in theory. An obvious solution is to obtain a stratified sample, where the stratifying variable is the geographical indication. In this case, the elements of the sample should be selected from the wines receiving marketing authorisation during a given wine year. Taking a full year into account can eliminate potential distortions due to the seasonality of the supply (for example, new wines for quick consumption appear on the market in

November each year, Egri Csillag wines on March 15 each year, full-bodied red wines usually in the spring of the second year after harvest).

It may be a problem that each layer shall reach a minimum number of elements (30-40) which is not expected to be the case for smaller wine districts or less used geographical indications. Hence, there are two possibilities: to carry out a full examination of certain layers or exclude GIs where the layer size would be extremely small.

At present, 38 GIs are protected in Hungary, so with the inclusion of wines without GI, the research would require a total of 39 layers.

The relative size of each layer can be selected respecting representativeness in two ways: (1) proportional or (2) Neyman optimum layering. The following factors must be considered for optimal selection (Galambosné Tiszberger, 2011, pp. 920-921):

- The relative size of each layer: in this case, the size of each layer will vary significantly
- The internal standard deviation of layers with the higher number of elements or lower number of layers: it is difficult to estimate the standard deviation in advance, but we can expect that smaller layers will have a higher standard deviation. In contrast, some larger layers will have higher, and others will have a smaller standard deviation.

With these considerations in mind, when designing the sample layers, the proportional allocation should be considered, and the following factors should be taken into account when selecting the layer size:

- the total quantity of wines marketed with the geographical indication in question (this is the total amount of batches expressed in litres),
- the number of wine batches marketed with that geographical indication.

Thus, a total of about 2-3,000 elements would be included in 39 layers following this method (as about 16-17,000 wines are submitted for marketing authorisation each year).

The elements of the sample shall be identified with the marketing authorisation identifier guaranteeing that information is not lost during price monitoring.

Contrary to its many advantages, stratified sampling has several serious drawbacks. Obtaining information on the prices of wines in the sample may be accidental, and there are severe concerns about price comparability due to the different distribution channels. Besides, the use of this sampling procedure may result in involving batches that are not available in Hungary, as they may be wholly sold abroad.

Accordingly, an excellent alternative to stratified sampling may be the selection of a commercial channel and the pursuit of greater immersion there. For this study, this means practically the so-called off-trade sector (retail stores: e.g. supermarket, hypermarket, specialised wine shop). The price taken into account is the lowest non-promotional gross price for a given wine item in the sector. The link between the different data sources is established upon the marketing authorisation identifier in this case, too.

Commercial sampling should be carried out at the time of the slightest possible distortion due to seasonality; when light, fresh, not aged (e.g. summer rosé) and more mature wines are present. This is practically the end of the second quarter and the beginning of the third quarter. The primary implementation risk of this sampling method is the unknown willingness of potential partners to cooperate.

Table 23

Arguments for and against the use of each presented sampling method

Sampling method	Arguments for	Arguments against
Stratified sample	• representative regarding the population • IID sample	• wines that are not present in the Hungarian market may be sampled • prices may not be comparable due to possibly different sales channels • the will of the data owners to cooperate • fragmented data collection that is hard to organise • the observation of the price may be based on self-declaration • some GIs may be excluded from the sample
sample from the commerce	• a significant proportion of the population may be included in the sample when selecting the proper sales channel • concentrated data collection at cooperating partners	• may be representative to only the selected commercial channel • the will of the data owners to cooperate • some GIs may be excluded from the sample
wine contest	• collection of data from one source • inclusion of expert ratings in the model	• data collection on self-declaration, hard to validate • the constitution of the sample is the function of producers' decision

Source: Own composition.

Another alternative way of sampling is to cooperate with a significant wine competition. This method seems to be a good idea, as the organisers will already, in principle, request the most necessary data from the candidates. Moreover, in this case, the expert scores would be available, too, from the most uniform source available in practice. Another benefit is that it is sufficient to agree with one actor on the use of the data. However, the choice of this route is already close to the convenience sample. The representativeness of the sample is questionable, to put it mildly (participation in the wine competition itself depends on the producer's decision) and the data would be based on self-declaration. Validation of self-reported data is possible by cross-checking (with data from the wine authority). However, controlling the most critical variable (price) would entail all the disadvantages of commercial sampling.

The arguments for and against the use of each alternative sampling method are summarised in Table 23.

3.5.2 Sampling

Taking into account what was described in the previous section, the sample required for the research was taken from commerce directly.

Sampling took place in the 3rd quarter of 2016 within the framework of the GI programme of the Ministry of Agriculture of Hungary in the following commercial units in the metropolitan area of Budapest: TESCO Budaörs, SPAR Budapest MOM Park and Interspar Budapest Allée, CBA Budapest 2nd district, Borháló Budapest 8th district, Bortársaság stores, In Vino Veritas stores, Lidl Budapest 10th district and Radovin Budapest, 13th district.

If a wine was observed on multiple sites, the lowest list price was included in the dataset.

3.5.3 Presentation of the sample

Following the clearing of the sample, 2,672 wines remained, produced by 392 wineries. The descriptive statistics are summarised by Table 24. The sample represents about 20% of wines marketed in one year both in terms of the quantity of wines (536 669 hl) and the number of lots.

Table 24

Descriptive statistics – first step

Variable	Observations	Mean	Std. deviation	Min	Max	Unit of measurement
Price	2672	2693.23	5856.22	194.85	194330	HUF/0.75 litre
Lot size	2672	20084.92	39199.50	120	607568	litre
Sugar	2672	13.22216	37.67	0	578	gram/litre
Sugar free extract	2672	25.58	6.89	15.6	124.6	gram/litre
Age	2672	2.54	1.92	1	17	year

Source: own calculation

Table 24 does not include the dummy variables due to size reasons. For their descriptive statistics, see Table I.1 of Appendix I.

The sample used in the first step of the study contained 33 of the 37 then existing Hungarian wine GIs. However, 5 GIs had to be omitted due to the low number of wines in the sample. Given the specification of the models and the representativeness, only GIs represented by at least six wines and at least 30% of the number of wines marketed in the last year preceding the year of data collection received their own dummy variable. were included in the sample. The items concerned were not excluded from the sample, but the relevant GI dummies were not included in the models.

Moreover, as mentioned in subsection 3.4.1.1, and given the extreme levels of sugar content and relatively high prices, all wines originating in the Tokaj region were excluded from the sample (as they would majorly distort the results) when applying LVPLS. Therefore, that sample consisted of 2,308 wines. Furthermore, all GIs in the sample were represented in this model, regardless of their low number or proportion. Descriptive statistics and measurement units regarding the LVPLS model are shown in Table I.2 of Appendix I.

Table 25

Descriptive statistics of the second step – models "C"

Variable	Obs.	Mean	Std. deviation	Min	Max	Unit of measurement
Mean price (log)	28	7.54	0.45	6.22	8.83	HUF/0.75 litre
Estimated implicit price (model A1)	28	127.11	28.45	64.44	220.10	-
Estimated implicit price (model A4)	28	121.65	27.31	57.73	195.68	-
Maximal level of yield	28	102.32	7.87	85	120	hectolitres per hectare
Group heterogeneity	28	19.28	35.49	0.29	188.87	hectolitre
Barrier to entry	28	21.10	11.01	5.21	49.14	%
Land quality	28	298.68	34.15	219	333	points

Source: own calculation

In the second step of the study the units of observation are geographical indications. As a consequence of the different approaches towards geographical indications that are segmented into two or three quality levels (detailed in sections 3.4.1 and 3.4.2), models “C” and “D” use different set of data, hence the difference in the descriptive statistics illustrated by Tables 25 and 26.

Table 26

Descriptive statistics of the second step – models “D”

Variable	Obs.	Mean	Std. deviation	Min	Max	Unit of measurement
Mean price (log)	33	7.69	0.64	6.22	9.73	HUF/0.75 litre
Estimated implicit price (model B1)	33	135.89	36.57	62.90	224.34	-
Estimated implicit price (model B4)	33	133.28	36.02	55.76	222.31	-
Maximal level of yield	33	96.67	17.49	35	120	hectolitres per hectare
Group heterogeneity	33	18.20	33.36	0.29	188.87	hectolitre
Barrier to entry	33	22.87	11.73	5.21	49.14	%
Land quality	33	301.85	32.71	219	333	points

Source: own calculation

4 RESULTS

The results of the models of both steps are presented in this chapter.

4.1 First step

In the first step, the impact of the factors on wine prices was estimated. The regression analyses were first carried out in a restricted manner, then extended models containing all variables were calculated. Thus, it was possible to estimate the difference in the gross and net shadow prices of GIs.

The numbering of the models follows the rule set out in Table 11; however, an additional number is added to the code (A1-A6 and B1-B6) specified therein, depending on whether the models are restricted (X.RY) or extended (X.2-X.7). In each case, models X.7 (e.g. B1.7) contain all the observed factors.

The numbering of restricted models complies with the number of the relevant hypothesis as follows:

R1. Geographical indications

R2. Individual brands

R3. Chemical composition

R4. Age of the wine

R5. Batch size (quantity)

R6. Colour and varietal

In case of models A1 and B1, new variables were included step by step (reflecting the suggestion of Thrane, 2004), in the following sequence:

1. Geographical Indications (restricted models)
2. Vineyard names (crus)
3. Individual brands
4. Chemical composition
5. Age of the wine
6. Batch size (quantity)

7. Colour and varietal

For space reasons, in the case of models A2-A6 and B2-B6, only the results of the restricted models and the most extended models (taking into account all variables) are reported here. As the dependent variable is the natural logarithm of the price, the impact of dummies (GIs, crus, individual brands, colour and varietal) expressed in percentage can be calculated using the following formula:

$$X_i = \left(e^{ß_i} - 1\right) * 100$$

where:

X: the impact of the dummy variable *i* expressed in percentage,

$ß_i$: the estimated coefficient of dummy *i*.

4.1.1 Results of restricted models

Results of models restricted robust standard errors regression models (models 1.R2-R6) and restricted quantile regression models (models from No. 2.R2-R6 to No. 6.R2-R6) are presented in this section. Note, that these models do not include geographical indications, therefore, the results of approaches A and B are identical. Restricted models containing GIs presented in different sections.

Table 27

Results of restricted robust standard error models 1.R2-6

Variable	model 1.R2	model 1.R3	model 1.R4	model 1.R5	model 1.R6
Tier1 individual brand	0.5039***				
Tier2 individual brand	0.5759***				
Sugar free extract (quadratic)		0.0006***			
White*Sugar		0.0018			
Non-white*Sugar		-0.0275***			
Age			0.2543***		
Lot size (log)				-0.3221***	
Red-Bordeaux variety					0.6470***
Red-other variety					0.3684***
Red-variety not indicated					-0.0702
White-other variety					0.5341***
White-variety not indicated					0.0370
Other Muscat variety					0.1826***
Cserszegi or Irsai					-0.1367***
Constant	7.2824***	7.0880***	6.8280***	10.3546***	7.0881***
R^2	0.1045	0.3054	0.3689	0.3073	0.0939
AIC	6.1e+03	5.4e+03	5.2e+03	5.4e+03	6.2e+03
BIC	6.1e+03	5.5e+03	5.2e+03	5.4e+03	6.2e+03

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

Table 27 provides the results robust standard errors regression models that confirm hypothesises H1.2-H1.6 of the first step.

Table 28

The results of restricted quantile regression models including variables on individual brands (models 2.R2-6.R2)

Variable	1st decile	1st quartile	Median	3rd quartile	9th decile
Tier1 individual brand	0.7174***	0.4193***	0.3043***	0.4733***	0.6692***
Tier2 individual brand	0.8620***	0.5108***	0.3897***	0.5012***	0.4677***
Constant	6.3081***	6.8669***	7.3065***	7.6958***	8.2251***
Pseudo R^2	0.1096	0.0722	0.0462	0.0408	0.0435

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

Individual brands (model 1.R2 in Table 27 and models 2.R2-6.R2 presented in Table 28) have a tremendous impact on prices. Interestingly, the extent of the impact of 2nd tier brands is larger than that of 1st tier brands in almost all of the cases. The gap is the most significant in the lowest segment (at the 1st decile) and decreases as the prices increase. Moreover, in the highest segment, the coefficient of 1st tier brands exceeds that of 2nd tier brands. The impact is the smallest at the median (+36% for Tier 1 brands and +48% for Tier 2 brands) and the highest at the 1st decile (+105% and +137%, respectively).

Table 29

The results of restricted quantile regression models including variables on chemical composition (models R3)

Variable	1st decile	1st quartile	Median	3rd quartile	9th decile
Sugar free extract (quadratic)	0.0006***	0.0007***	0.0008***	0.0011***	0.0013***
White*Sugar	-0.0014	0.0005	0.0007	0.0005	0.0004
Non-white*Sugar	-0.0438***	-0.0303***	-0.0312***	-0.0254***	-0.0233***
Constant	6.3461***	6.6857***	6.9671***	7.1237***	7.4358***
Pseudo R^2	0.1094	0.1268	0.1593	0.2176	0.2601

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

The impact of variables describing the chemical composition is in line with hypothesis H1.3, however not in all cases (model 1.R3 in Table 27 and models 2.R3-6.R3 presented in Table 29). The higher the sugar-free extract content is, the higher the prices are, and the magnitude of the impact is increasing as prices rise. Note, that the coefficients are calculated for the square of the sugar-free extract content; therefore, the effect is more extensive than it first seems: e.g. at the median, wines with an additional gram of sugar-free extract cost 4.1% more. The estimated impact of sugar is statistically non-significant for white wines in all cases, and negative for rosés and reds in all segments. The magnitude of the latter declines as the price increases: rosés and reds containing an additional gram of sugar cost 4.38% less in the lowest segment, and 2.33% less in the highest.

Table 30

The results of restricted quantile regression models on age (models R4)

Variable	1st decile	1st quartile	Median	3rd quartile	9th decile
Age	0.2275***	0.2130***	0.2245***	0.2866***	0.3499***
Constant	6.0825***	6.5311***	6.9456***	7.1400***	7.3279***
Pseudo R^2	0.1297	0.1232	0.1737	0.2647	0.3177

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

Results (model 1.R4 in Table 27 and models 2.R4-6.R4 presented in Table 30) show that older wines cost more. The effect of age increases as prices grow (except for the 1st decile and quartile), while wines with an extra year of ageing cost 21% more in the 1st quartile, the effect is 35% in the top segment.

Table 31

The results of restricted quantile regression models on quantity (models R5)

Variable	1st decile	1st quartile	Median	3rd quartile	9th decile
Lot size (log)	-0.3356***	-0.3080***	-0.2968***	-0.3058***	-0.3564***
Constant	9.7389***	9.7944***	10.0541***	10.5232***	11.4793***
Pseudo R^2	0.2710	0.2152	0.1621	0.1494	0.1087

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

Results of models containing lot size (model 1.R5 in Table 27 and models 2.R5-6.R5 presented in Table 31) show that wines sold in higher quantity cost less. The effect is the highest at the bottom and top segments. At the median, an additional 1% of the lot size means a 0.3% drop in the price.

Colour and varietal composition show a very complex image (model 1.R6 in Table 27 and models 2.R6-6.R6 presented in Table 32). Red wines made of Bordeaux varietals consistently cost more than the wines in the reference category (rosés) and the impact rises as prices rise (+34% at the bottom and +234% at the top segment).

Red wines made of other varietals have a negative shadow price at the lowest segment (-18%), which soon turns to positive and increases further as the price rises (15-137%).

The same scheme appears in the case of red wines without any indication of variety. Here, the coefficient is negative for the lower segments (-66% and -67%), statistically insignificant at the median and the mean, and turns to positive at the higher segments.

Table 32

The results of restricted quantile regression models including variables on colour and varieties (models 2.R6-6.R6)

Variable	1st decile	1st quartile	Median	3rd quartile	9th decile
Red-Bordeaux variety	0.2910***	0.3368***	0.4695***	0.8255***	1.2045***
Red-other variety	-0.1959*	0.1399***	0.2693***	0.6181***	0.8641***
Red-variety not indicated	-1.0914***	-1.1107***	0.0000	0.4242***	0.9057***
White-other variety	0.1913**	0.1957***	0.2693***	0.6282***	1.0933***
White-variety not indicated	-0.8746***	-0.9960***	-0.0036	0.5975***	1.1792***
Other Muscat variety	-0.1105	0.0000	0.0392	0.2033***	0.5114***
Cserszegi or Irsai	-0.1093	-0.2234***	-0.2231***	-0.1280**	-0.0625
Constant	6.5058***	6.9068***	7.2262***	7.3715***	7.4950***
Pseudo R^2	0.0746	0.0434	0.0489	0.0941	0.1077

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

This confirms the hypothesis that red wines cost more. However, wines without any information on the varietal form a heterogeneous group, as they are among the cheapest ones in the lower segments but benefit of serious price premia in the high end. The opposite effect of the lack of information on the variety at the two ends of the market may be due to the irrelevance of this factor in these segments and highlights the importance of the colour in the same time.

Price premia for white wines show a similarly mixed picture. The pattern for white wines with no information on the varietal is the same as in the case of red wines. The situation of the two groups of aromatic whites differs significantly. Wines from the two fashionable varieties (Cserszegi fűszeres and Irsai Olivér) have negative price premia in the middle of the market (-20%; -20% and -12%), while wines of other aromatic varietals have positive price premia in the higher segments (+23% and +67%). Whites from other varieties have positive and increasing estimated price premia - their situation is more or less comparable to reds from other varieties.

The explanatory value[9] of restricted models is moderate; however, we can observe significant differences among them. The value is higher in the case of models involving non-labelled parameters (chemical composition, age and quantity - the

[9] STATA Software Package uses Efron's formula for calculating pseudo-R^2, which is suitable to measure the percent variance explained (Hardin and Hilbe, 2007, p. 60).

values of R^2 are around 30%, and the values of pseudo-R^2 are about 10-20%), and lower in the case of elements indicated on the label (individual brands, varieties).

Moreover, the explanatory power of the quantile regression models increases as we move toward higher quantiles in the case of chemical composition, age, colour and varieties, and decreases in the case of quantity and individual brands. This suggests that differences in quantity and individual brand value have larger effects on the price in the lower end of the market, while differences in chemical composition, age, colour and varieties affect the prices to a greater extent in the top segments.

4.1.2 Models A1

Results of models A1R1.1-7 are presented in Table 33. These robust standard error regression models treat geographical indications that are segmented into two or three quality levels using additional terms to the name itself as one single name.

The results of these models confirmed all hypothesises (H1.1-H1.6). Here, I analyse the most extended models in detail and compare them to the restricted ones.

The models showed a positive price premium for 20 geographical indications out of the 28 observed (which is in line with H1.1). Besides, the value of the price premium was negative for one GI. The differences in the estimated coefficients of restricted and extended models show that GIs may incorporate important other factors like chemical composition, lot size, age or individual brands. In most cases (26 of 28), the GI coefficient was positive in the restricted model – except for Duna-Tisza közi (negative) and Dunántúl (insignificant).

The results underline that producers tend to position their single vineyard wines high as the indication of a vineyard's name raised the price by 52%.

This approach revealed that prices had a strong and robust relation to individual brands (confirming H1.2; +51% for the 1st Tier and +35% for the 2nd Tier). The premia of individual brands decreased by 15 and 43 percentage points compared to the relevant restricted model.

The models show that chemical composition is positively related to the price (H.1.3); an additional gram of sugar-free extract to the average of 25.58 g/l would cost 0.71% more (a decrease of 2.5 percentage points compared to the relevant restricted model). White wines with an additional gram of sugar cost 0.34% more (and is significant, which is not the case in the relevant restricted model), while reds and rosés 0.68% less (a decrease of 2.07 percentage points in the absolute value compared to the relevant restricted model).

Table 33

Results of models A1.R1 and A1.2-7

Variable	A1.R1	A1.2	A1.3	A1.4	A1.5	A1.6	A1.7
Single vineyard wine		0.7756***	0.7019***	0.8136***	0.6557***	0.4145***	0.4218***
Tier1 individual brand			0.3520***	0.3182***	0.2877***	0.4048***	0.4103***
Tier2 individual brand			0.4000***	0.3259***	0.2890***	0.2977***	0.2982***
Sugar free extract (quadratic)				0.0004***	0.0002***	0.0002***	0.0001**
White*Sugar				0.0028***	0.0026***	0.0026***	0.0034***
Non-white*Sugar				-0.0150***	-0.0130***	-0.0058***	-0.0068***
Age					0.1558***	0.1354***	0.1309***
Lot size (log)						-0.2280***	-0.2296***
Red-Bordeaux variety							0.0628*
Red-other variety							-0.0942***
Red-variety not indicated							-0.1310**
White-other variety							-0.1093***
White-variety not indicated							-0.1564**
Other Muscat variety							-0.1515***
Cserszegi or Irsai							-0.0795**
Badacsony	0.8541***	0.8541***	0.7372***	0.6052***	0.5391***	0.3000***	0.3140***
Balaton	0.3527***	0.3527***	0.3420***	0.3114***	0.3677***	0.3532***	0.3263***
Balatonboglár	0.5729***	0.5179***	0.4615***	0.3251***	0.3359***	0.2767***	0.2412***
Balaton-felvidék	0.5539***	0.5539***	0.5691***	0.4164***	0.5608***	0.2665***	0.2710***
Balatonfüred-Csopak	0.7078***	0.6509***	0.5539***	0.4451***	0.5101***	0.3042***	0.2860***
Bükk	0.6744***	0.6744***	0.7338***	0.6642***	0.7404***	0.2269	0.2164
Duna	0.4599**	0.4599**	0.5192**	0.3402*	0.3739***	0.1111	0.0889
Dunántúli	0.0776	0.0776	0.0257	0.0052	0.1221	0.1865***	0.1526**
Duna-Tisza közi	-0.7893***	-0.7893***	-0.7451***	-0.7900***	-0.6460***	-0.4430***	-0.4394***
Eger	0.7298***	0.6540***	0.5839***	0.4139***	0.2731***	0.3217***	0.3195***
Etyek-Buda	0.5055***	0.4938***	0.4546***	0.3687***	0.4146***	0.3615***	0.3534***
Felső-Magyarország	0.4134***	0.3998***	0.3379***	0.2953***	0.3283***	0.2027***	0.1840***
Hajós-Baja	0.2745**	0.2745**	0.3339***	0.1338	0.1419	0.1256	0.0775
Káli	1.2758***	1.2758***	1.3352***	1.1014***	1.0779***	0.8270***	0.7889***
Kunság	0.2976***	0.2894**	0.2447**	0.1061	0.1514*	-0.0339	-0.0593
Mátra	0.2230**	0.2230**	0.1941*	0.0991	0.1392	0.0195	-0.0042
Mór	0.4745***	0.4745***	0.5053***	0.4250***	0.5534***	0.2702***	0.2717***
Nagy-Somló	0.8569***	0.8569***	0.8256***	0.6746***	0.6382***	0.3719***	0.3985***
Neszmély	0.5128***	0.4423***	0.1883	0.1093	0.2232**	0.1814**	0.1767**
Pannon	0.3224***	0.3224***	0.2989***	0.2114**	0.3349***	0.3331***	0.2817***
Pannonhalma	0.7370***	0.7370***	0.5702***	0.5201***	0.6988***	0.5575***	0.5334***
Pécs	0.5769***	0.5769***	0.6285***	0.4605***	0.4831***	0.2469***	0.2309***
Sopron/Ödenburg	0.9230***	0.8998***	0.7703***	0.6574***	0.6686***	0.3502***	0.3169***
Szekszárd	0.7760***	0.7463***	0.6508***	0.4745***	0.4404***	0.3280***	0.2792***
Tokaj	1.3184***	1.2420***	1.1535***	0.5550***	0.4688***	0.3621***	0.3735***
Tolna	0.3603**	0.3603**	0.4087***	0.2727**	0.2033*	0.0529	0.0175
Villány	0.8628***	0.8381***	0.7005***	0.5271***	0.4905***	0.4384***	0.3892***
Zala	0.5610***	0.5610***	0.2341	0.1532	0.1981**	-0.0211	-0.0312
Constant	6.8311***	6.8311***	6.7718***	6.6571***	6.4390***	8.6235***	8.7581***
R^2	0.2950	0.3285	0.3733	0.5552	0.6223	0.7395	0.7453
AIC	5500	5400	5200	4500	3900	2900	2848
BIC	5700	5600	5400	4700	4100	3100	3108
VIF	1.96	1.93	1.90	2.03	2.03	2.02	2.11

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

Older wines cost more (H1.4), the impact of an additional year of ageing is 13.09% (a decrease of 12.34 percentage points compared to the relevant restricted model).

The relation of the lot size and the price is negative (H1.5), with 1% of the increase in quantity the prices decrease by 0.23% (a decrease of 0.9 percentage points compared to the relevant restricted model).

The price premium of red wines made of Bordeaux varieties is 6%, while the premium for all other varietal groups is negative (between -8% and -14%), which is mainly (but not fully) in line with hypothesis H1.6. The coefficients of the variables describing colour and varietals decreased to the highest extent compared to the relevant restricted model. Three of these variables changed signs and became negative, meaning that the price premia of these factors totally adsorbed by other variables of the model.

The explanatory value of the models increases by the inclusion of new variables, with the value of R^2 changed from 0.2950 to 0.7453. Therefore, the final extended model explains almost ¾ of the variance of the prices.

The estimations of these models show that 7 GI coefficients lose their statistical significance by adding new variables to the restricted model; however, 1 turns into significant. In most cases (18), the GI-coefficient estimated by the restricted model decreased in the extended model (by 24 to 72%). In two cases (Balaton and Pannon), the GI-coefficient slightly increased from the restricted to the extended model.

4.1.3 Models A2-A6

Results of models A2-A6.R1 (restricted models containing only GI dummies) and 7 (extended models containing all variables) are presented in Table 34. These quantile regression models treat geographical indications that are segmented into two or three quality levels using additional terms to the name itself as one single name.

Table 34. Results of models A2-A6 (restricted and extended models)

Variable	A2.R1 (1st decile)	A2.7 (1st decile)	A3.R1 (1st quartile)	A3.7 (1st quartile)	A4.R1 (Median)	A4.7 (Median)	A5.R1 (3rd quartile)	A5.7 (3rd quartile)	A6.R1 (9th decile)	A6.7 (9th decile)
Single vineyard wine		0.4813***		0.4038***		0.3970***		0.3178***		0.4231***
Tier1 individual brand		0.4282***		0.3919***		0.3860***		0.3902***		0.4315***
Tier2 individual brand		0.2911***		0.3356***		0.2922***		0.2901***		0.2920***
Sugar free extract (quadratic)		0.0001*		0.0002***		0.0002***		0.0002***		0.0002***
White*Sugar		0.0955***		0.1162***		0.1195***		0.1432***		0.1872***
Non-white*Sugar		0.0038***		0.0024***		0.0032***		0.0028***		0.0024***
Age		-0.0032		-0.0050***		-0.0067***		-0.0080***		-0.0074***
Lot size (log)		-0.2204***		-0.2183***		-0.2182***		-0.2188***		-0.2025***
Red-Bordeaux variety		0.0005		-0.0152		0.0136		0.0372		0.1590***
Red-other variety		-0.1517***		-0.1139***		-0.1130**		-0.0913**		-0.0283
Red-variety not indicated		-0.1306		-0.1920***		-0.2336***		-0.1672**		-0.0549
White-other variety		-0.1306***		-0.1007***		-0.0939**		-0.1021**		-0.0578
White-variety not indicated		-0.2515**		-0.1730**		-0.1016		-0.091		-0.1645
Other Muscat variety		-0.1506**		-0.1278**		-0.1554**		-0.2118***		-0.1979***
Cserszegi or Irsai		-0.1118		-0.0549		-0.0969		-0.1015		-0.1019
Badacsony	1.3888***	0.6464***	1.4575***	0.4622***	0.8484***	0.2324**	0.4568***	0.3416***	0.2836	0.0794
Balaton	0.7750***	0.5995***	0.8283***	0.5391***	0.3681***	0.3096***	-0.0381	0.2934***	-0.2137	0.0638
Balatonboglár	1.0436***	0.4735***	1.1471***	0.4887***	0.5113***	0.2190***	0.1466*	0.1674**	-0.0164	-0.0725
Balaton-felvidék	1.2023***	0.7317***	1.4581***	0.5202***	0.6371***	0.1479	-0.0159	0.174	-0.5172**	-0.0179
Balatonfüred-Csopak	1.2071***	0.5817***	1.4515***	0.5320***	0.6937***	0.3119***	0.2744***	0.2147**	-0.0057	-0.067
Bükk	0.9829***	0.5738***	1.6405***	0.3818**	0.6943***	0.2208	0.0463	0.0391	0.0267	0.4054***
Duna	1.2073***	0.3408***	1.0527***	0.2682	0.4066***	-0.1549	0.1001	0.089	-0.1425	-0.2517*
Dunántúli	0.6003***	0.5362***	0.5402***	0.4098***	0	0.0884	-0.2371**	-0.0085	-0.4512**	-0.2184*
Duna-Tisza közi	-0.2860***	-0.1167	-0.1546***	-0.3000***	-0.8905***	-0.5494***	-1.1543***	-0.5237***	-1.4980***	-0.5783***
Eger	0.8492***	0.5957***	1.2266***	0.4886***	0.6365***	0.3002***	0.4564***	0.2877***	0.3493**	-0.008
Etyek-Buda	1.0436***	0.6454***	1.2342***	0.5709***	0.4422***	0.3909***	-0.0005	0.2997***	-0.0557	0.009
Felső-Magyarország	0.5705***	0.3604***	0.9462***	0.4009***	0.4641***	0.2407***	0.1669*	0.1404	-0.1554	-0.1846*
Hajós-Baja	1.1008***	0.5284***	1.0527***	0.2964***	0.3208***	0.0611	-0.2374*	0.0261	-0.6130***	-0.1492
Káli	1.6456***	1.0942***	2.0823***	1.1052***	1.1984***	0.6713***	0.8620***	0.9477***	0.7612***	0.5523***
Kunság	0.9829***	0.3114***	1.0527***	0.1648**	0.3296***	-0.0436	-0.2371**	-0.1168	-0.6643***	-0.3669***
Mátra	0.6965***	0.4352***	0.7637***	0.2602***	0.2804***	-0.0063	-0.1725*	-0.0961	-0.5176***	-0.3259***
Mór	1.3813***	0.8496***	1.2342***	0.6596***	0.5113***	0.252	-0.2364	0.0945	-0.6125**	-0.2621
Nagy-Somló	1.1008***	0.7066***	1.4575***	0.6885***	0.8949***	0.3813***	0.5936***	0.4243***	0.0294	0.1245
Neszmély	1.2889***	0.5770***	1.2342***	0.4494***	0.4422***	0.1321	-0.0272	0.0446	-0.5927***	-0.2691*
Pannon	1.1871***	0.6702***	1.1471***	0.5628***	0.4066***	0.2875*	-0.2431	0.2417*	-0.7756***	-0.0281
Pannonhalma	1.4697***	0.9438***	1.5833***	0.8239***	0.7991***	0.5199***	0.2744**	0.4763***	-0.2137	0.0813
Pécs	1.2073***	0.6662***	1.1480***	0.5253***	0.5119***	0.1821*	-0.0005	0.1048	-0.3127	-0.0403
Sopron/Ödenburg	1.5438***	0.7658***	1.4581***	0.6466***	0.7640***	0.3203***	0.6109***	0.1524	0.3138*	-0.1625
Szekszárd	1.2063***	0.6184***	1.4311***	0.5228***	0.7430***	0.2826***	0.3551***	0.2199***	0.0804	-0.1094
Tokaj	1.3017***	0.5530***	1.6123***	0.5518***	1.2017***	0.3033***	1.1497***	0.4214***	1.2960***	0.2612***
Tolna	0.6319***	0.2201	1.0426***	0.1598	0.4780***	0.0098	-0.1533	-0.0078	-0.2513	-0.3893**
Villány	1.2063***	0.7258***	1.3884***	0.5936***	0.7738***	0.3746***	0.5306***	0.3125***	0.4348***	-0.0034
Zala	1.2063***	0.5909***	1.3143***	0.2672*	0.5759***	0.0092	0.0672	-0.2617	-0.4385**	-0.5101***
Constant	5.7004***	8.0136***	5.8551***	8.2062***	6.8013***	8.6612***	7.5496***	8.8957***	8.2134***	9.0926***
Pseudo-R^2	0.2735	0.5152	0.2039	0.4848	0.1433	0.4719	0.1645	0.5053	0.2011	0.5499
VIF	1.00	2.74	1.00	2.74	1.00	2.74	1.00	2.74	1.00	2.74

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

The results of these models confirmed hypothesises H1.1-H1.5 and partially H1.6. The models showed a positive price premium for 3-26 geographical indications out of the 28 observed (which is in line with H1.1). Besides, the value of the price premium was negative for 0-9 GIs depending on the model. The results clearly show that the price premia of GIs are generally and gradually decreasing as we move towards the higher price segments (26, 25, 16, 13 and finally 3 GIs have positive premia for percentiles 10, 25, 50, 75 and 90) and then “runs out” for most GIs. In an increasing number of cases, the premium even turns negative (0, 1, 1, 1 and finally 9 GIs for percentiles 10, 25, 50, 75 and 90). The estimations of these models show that the number (1, 2, 10, -1 and 2 for percentiles 10, 25, 50, 75 and 90) of GI dummies losing their statistically significant positive coefficients by adding new variables to the restricted model is the highest at the median (the coefficient of Balaton is not statistically significant at the 3rd quartile in the restricted model, but it is positive in the most extended model). However, PDO Bükk replaces PDO Sopron/Ödenburg at the ninth decile in the group of GIs with a positive price premium. Moreover, in most cases, the GI-coefficient estimated by the restricted model decreased in the extended model.

In the medium segment (at the median), PDO Káli has the highest premium (+ 97%), but Pannonhalma (+68%), Villány (+45%), Etyek-Buda (+48%) and Nagy-Somló (+46%) have to be mentioned as well. Premia for popular GIs like Eger and Tokaj decreases to +35% for the median. Labelling vineyard names is reflected in wine prices in all segments, with prices of single-vineyard wines is 37-62% higher than other wines.

The differences in the estimated coefficients of restricted and extended models show in the case of these models, too, that GIs may incorporate important other factors like chemical composition, lot size, age or individual brands. Having the only negative sign, the absolute value of the coefficient of Duna-Tisza közi is much higher in the lowest segment in the restricted model than in the extended one, illustrating that the incorporation of other factors works the other way around as well. Decrease of the price premium (even to zero) and even its turning into negative towards higher segments can be observed in the extended models, too.

This approach confirmed, too that prices had a strong and robust relation to individual brands (in line with H1.2; +47-54% for the 1st tier and +34-40% for the 2nd tier). The premium of Tier1 was the highest at the two ends of the market, while for Tier2, at the first quartile. These estimated coefficients are considerably lower (4-51 and 14 to 103 percentage points, respectively) than those estimated by restricted models (No. 2R2-6R2). Thus, the expected order of the estimated coefficients of Tier1 and Tier2 individual brands has been restored in the extended models in all quantiles.

As H1.3 suggested, the sugar-free extract is positively related to the price, while the sugar content has a controversial impact on white and non-white wines. An additional gram of the sugar-free extract would cost more and more as the price increases (0.4%, 0.8%, 1.0%, 1.4% and 1.4% for percentiles 10, 25, 50, 75 and 90), however, the extent is considerably lower than estimated by the restricted models (to its one sixth-one fifth part). The positive impact of an additional gram of sugar content on white wine prices decreases with the growth of the price (from 0.38% in the first decile to 0.24% in the ninth). Meanwhile, the negative impact of an additional gram of sugar on rosés and reds grows along with the price (it is not significant in the first decile, then the absolute value increases from 0.5% in the first quartile to 0.74% in the ninth decile). The relevant restricted models estimated that the impact of sugar on white wine prices was statistically insignificant. However, the effect on rosé and red prices was estimated much worse by the relevant restricted models.

Older wines cost more, the impact of an additional year of ageing is 9.5-19% and increases with the price (confirming H1.4). The impact has decreased by 10 to 16 percentage points compared to the relevant restricted models.

The relation of the lot size and the price is negative, with 1% of the increase in quantity the prices decrease by 0.21-0.23% (the highest at the first decile, the second-highest at the median and the lowest at the ninth decile – confirming H1.5). The impact decreased by 0.08 to 0.15 percentage points compared to the relevant restricted models.

The hypothesis on the role of colour and varieties (H1.6) was not confirmed unambiguously. The expected positive price premium for red wines was only present in case of Bordeaux varietals and only for the ninth decile. Other red categories were estimated to have a negative price premium in all quantiles except for the nine decile. The situation was similar for the white wines as well, albeit the models estimated statistically non-significant coefficients for Cserszegi or Irsai in all quantiles. The estimated coefficients for the variables reflecting colour and varietals were considerably higher in all relevant restricted models (except for Cserszegi or Irsai).

This suggests that in the reality, some other factors explain the differences in wine prices that seemed to be caused by varietal composition.

The explanatory value of the models increases by the inclusion of new variables, with the value of pseudo-R^2 increases to 0.4719-0.5499. Therefore, the final extended model explains about half of the variance of the prices.

4.1.4 Models B1

Results of models B1.R1-7 are presented in Table 35. These robust standard error regression models treat geographical indications that are segmented into two or three quality levels using additional terms to the name itself as multiple separate names (depending on the actual number of quality levels).

The results of these models confirmed all hypothesises (H1.1-H1.6). The models showed a positive price premium for 26 geographical indications out of the 33 observed (which is in line with H1.1). Besides, the value of the price premium was negative for one GI.

The differences in the estimated coefficients of restricted (to GIs) and extended models show that at first glance, GIs may incorporate important other factors like chemical composition, lot size, age or individual brands. In most cases (31 of 33), the GI coefficient was positive in the restricted model (except for Duna-Tisza közi [negative] and Dunántúl [zero]).

The results underline that producers tend to position their single vineyard wines high as the indication of a vineyard’s name raised the price by 47%.

This approach revealed that prices had a strong and robust relation to individual brands (confirming H1.2; +49% for the 1st tier – a 17 percentage point drop compared to the relevant restricted model – and +34% for the 2nd tier – a 38 percentage point drop compared to the relevant restricted model).In the final extended model, the relation of the two tiers is in line with the expected due to a major decrease in the estimated value of the 2nd tier. It seems that the unexpected difference between the two variables was mainly due to other factors.

Table 35

Results of models B1.R1-7.

Variable	B1.R1	B1.2	B1.3	B1.4	B1.5	B1.6	B1.7
Single vineyard wine		0.6879***	0.6278***	0.6713***	0.5781***	0.3776***	0.3849***
Tier1 individual brand			0.3116***	0.2841***	0.2661***	0.3898***	0.3955***
Tier1 individual brand			0.3600***	0.3162***	0.2849***	0.2935***	0.2943***
Sugar free extract (quadratic)				0.0003***	0.0002***	0.0001***	0.0001**
White*Sugar				0.0027***	0.0028***	0.0024***	0.0032***
Non-white*Sugar				-0.0149***	-0.0131***	-0.0060***	-0.0071***
Age					0.1380***	0.1213***	0.1166***
Lot size (log)						-0.2236***	-0.2255***
Red-Bordeaux variety							0.0636**
Red-other variety							-0.0782***
Red-variety not indicated							-0.1128*
White-other variety							-0.1106***
White-variety not indicated							-0.1138*
Other Muscat variety							-0.1448***
Cserszegi or Irsai							-0.0925**
Badacsony	0.8541***	0.8541***	0.7488***	0.6059***	0.5490***	0.3139***	0.3328***
Balaton	0.3527***	0.3527***	0.3429***	0.3068***	0.3596***	0.3462***	0.3250***
Balatonboglár	0.5729***	0.5241***	0.4743***	0.3456***	0.3503***	0.2869***	0.2555***
Balaton-felvidék	0.5539***	0.5539***	0.5679***	0.4195***	0.5480***	0.2616***	0.2705***
Balatonfüred-Csopak	0.7078***	0.6573***	0.5702***	0.4542***	0.5119***	0.3067***	0.2932***
Bükk	0.6744***	0.6744***	0.7277***	0.6434***	0.7212***	0.2188	0.2111
Duna	0.4599**	0.4599**	0.5132**	0.3507*	0.3774**	0.1201	0.0983
Dunántúli	0.0776	0.0776	0.0318	0.0038	0.1097	0.1733**	0.1420**
Duna-Tisza közi	-0.7893***	-0.7893***	-0.7494***	-0.7939***	-0.6648***	-0.4621***	-0.4636***
Eger Classicus	0.4401***	0.4299***	0.3730***	0.2311**	0.1898**	0.2901***	0.2820***
Eger Superior	1.4709***	1.2416***	1.1940***	0.9702***	0.7561***	0.6720***	0.6768***
Eger Grand Superior	1.8768***	1.5820***	1.3355***	1.1536***	1.0630***	0.6731***	0.6869***
Eger before 2010	1.4692***	1.2781***	1.2242***	1.0732***	0.3434**	0.2397*	0.2376*
Etyek-Buda	0.5055***	0.4951***	0.4607***	0.3637***	0.4094***	0.3555***	0.3509***
Felső-Magyarország	0.4134***	0.4013***	0.3458***	0.3010***	0.3297***	0.2052***	0.1867***
Hajós-Baja	0.2745**	0.2745**	0.3278***	0.1421	0.1472	0.1314	0.0888
Káli	1.2758***	1.2758***	1.3291***	1.1081***	1.0830***	0.8412***	0.8080***
Kunság	0.2976***	0.2903***	0.2514**	0.115	0.1541*	-0.0294	-0.0488
Mátra	0.2230**	0.2230*	0.1969*	0.0906	0.1309	0.0151	-0.0024
Mór	0.4745***	0.4745***	0.5021***	0.4074***	0.5299***	0.2551***	0.2614***
Nagy-Somló	0.8569***	0.8569***	0.8291***	0.6784***	0.6471***	0.3838***	0.4144***
Neszmély	0.5128***	0.4502***	0.2257*	0.1382	0.2344**	0.1835**	0.1867**
Pannon	0.3224***	0.3224***	0.3023***	0.2076**	0.3214***	0.3195***	0.2719***
Pannonhalma	0.7370***	0.7370***	0.5867***	0.5100***	0.6755***	0.5400***	0.5232***
Pécs	0.5769***	0.5769***	0.6233***	0.4601***	0.4813***	0.2508***	0.2385***
Sopron/Ödenburg	0.9230***	0.9024***	0.7856***	0.6678***	0.6767***	0.3623***	0.3278***
Szekszárd	0.7760***	0.7497***	0.6646***	0.5027***	0.4649***	0.3488***	0.2984***
Tokaj wine speciality	2.2646***	2.2498***	2.1473***	0.9957***	0.6887***	0.6634***	0.6833***
Tokaj non-wine speciality	0.9692***	0.8818***	0.8112***	0.5173***	0.4670***	0.3439***	0.3597***
Tolna	0.3603**	0.3603**	0.4039***	0.2754**	0.2147*	0.0644	0.0322
Villány Classicus	0.5705***	0.5680***	0.4581***	0.3207***	0.3548***	0.3252***	0.2807***
Villány Pérmium	1.6922***	1.6150***	1.4547***	1.2171***	0.9694***	0.8359***	0.7709***
Zala	0.5610***	0.5610***	0.2681*	0.165	0.2051**	-0.0128	-0.0178
Constant	6.8311***	6.8311***	6.7778***	6.7223***	6.5007***	8.6380***	8.7709***
R^2	0.4349	0.4640	0.4996	0.5791	0.6431	0.7537	0.7588
AIC	4900	4800	4600	4200	3700	2800	2713
BIC	5100	5000	4900	4400	4000	3000	3001
VIF	1.83	1.81	1.79	1.95	1.96	1.95	2.05

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

The models show that chemical composition (sugar-free extract) is positively related to the price; an additional gram to the average of 25.58 g/l would cost 0.5% more (a decrease of 2.7 percentage points compared to the relevant restricted model). The role of sugar content is ambivalent; in the case of white wines, an additional gram of sugar results in 0.24% higher prices, while 0.7% lower prices in the case of rosés and reds (a decrease of 2.04 percentage points in the absolute value compared to the relevant restricted model). (H1.3).

Older wines cost more, the impact of an additional year of ageing is 11.66% (a decrease of 13.77 percentage points compared to the relevant restricted model – H1.4). The relation of the lot size and the price is negative, with 1% of the increase in quantity the prices decrease by 0.23% (a decrease of 0.11 percentage points compared to the relevant restricted model – H1.5).

The coefficients that model B1.7 estimated for the variables describing colour and varietal almost equal to those estimated by model A1.7.

The explanatory value of the models increases by the inclusion of new variables, with the value of R^2 increases from 0.4349 to 0.7588. Therefore, the final extended model explains slightly more than ¾ of the variance of the prices. The difference in the explanatory value of these models exceed those that treat GIs with multiple quality levels as one. However, the difference decreases with the addition of new variables.

The estimations of these models show that 7 GI coefficients lose their statistical significance by adding new variables to the restricted model; however, 1 turns into significant. In most cases (25), the GI-coefficient estimated by the restricted model decreased in the extended model (by 1 to 84%).

4.1.5 Models B2-B6

Results of models B2.R1 (restricted models containing only GI dummies) and 7 (extended models containing all variables) are presented in Table 36. These quantile regression models for the first decile treat geographical indications that are segmented into two or three quality levels using additional terms to the name itself as two or three separate names (depending on the actual number of quality levels).

Table 36. Results of models B2 -B6 (R1. restricted and extended models)

Variable	B2.R1 (1st decile)	B2.7 (1st decile)	B3.R1 (1st quartile)	B3.7 (1st quartile)	B4.R1 (Median)	B4.7 (Median)	B5.R1 (3rd quartile)	B5.7 (3rd quartile)	B6.R1 (9th decile)	B6.7 (9th decile)
Single vineyard wine		0.4315***		0.3571***		0.3593***		0.2442***		0.4796***
Tier1 individual brand		0.3941***		0.3967***		0.3810***		0.3585***		0.4144***
Tier1 individual brand		0.2859***		0.3190***		0.2917***		0.2724***		0.2957***
Sugar free extract (quadratic)		0.0001		0.0001***		0.0002***		0.0001***		0.0001***
White*Sugar		0.0039***		0.0027***		0.0028***		0.0034***		0.0039***
Non-white*Sugar		-0.0034*		-0.0053***		-0.0069***		-0.0090***		-0.0085***
Age		0.0808***		0.1035***		0.1097***		0.1250***		0.1694***
Lot size (log)		-0.2267***		-0.2180***		-0.2136***		-0.2081***		-0.1827***
Red-Bordeaux variety		-0.0148		-0.0053		0.0101		0.0864*		0.1844***
Red-other variety		-0.1652***		-0.0926**		-0.0969***		-0.0382		0.0094
Red-variety not indicated		-0.139		-0.1946***		-0.2159***		-0.0388		-0.0006
White-other variety		-0.1482***		-0.1054***		-0.0883***		-0.0816**		-0.0805**
White-variety not indicated		-0.2305**		-0.1454*		-0.0747		-0.078		-0.1819*
Other Muscat variety		-0.1599**		-0.0975*		-0.1323***		-0.2222***		-0.2037***
Cserszegi or Irsai		-0.1308		-0.0712		-0.0937**		-0.1086*		-0.0987
Badacsony	1.3888***	0.6570***	1.4575***	0.4559***	0.8484***	0.2463***	0.4568***	0.2728***	0.2836*	0.1055
Balaton	0.7750***	0.6675***	0.8283***	0.5139***	0.3681***	0.2954***	-0.0381	0.2765***	-0.2137	0.0239
Balatonboglár	1.0436***	0.5012***	1.1471***	0.4719***	0.5113***	0.2339***	0.1466*	0.1376*	-0.0164	-0.0807
Balaton-felvidék	1.2023***	0.7412***	1.4581***	0.4925***	0.6371***	0.1400*	-0.0159	0.1732	-0.5172**	-0.0339
Balatonfüred-Csopak	1.2071***	0.5904***	1.4515***	0.5049***	0.6937***	0.3137***	0.2744***	0.2055**	-0.0057	-0.0569
Bükk	0.9829***	0.5517***	1.6405***	0.3511*	0.6943***	0.2157	0.0463	0.0211	0.0267	0.4201***
Duna	1.2073***	0.3238**	1.0527***	0.2426	0.4066***	0.3471**	0.1001	0.0454	-0.1425	-0.1716*
Dunántúli	0.6003***	0.5524***	0.5402***	0.3819***	0	0.0732	-0.2371**	0.0132	-0.4512***	-0.2572***
Duna-Tisza közi	-0.2860***	-0.1117	-0.1546***	-0.3693***	-0.8905***	-0.5841***	-1.1543***	-0.5770***	-1.4980***	-0.6223***
Eger Classicus	0.6948***	0.5847***	1.0426***	0.4309***	0.5113***	0.2708***	0.0612	0.2041**	-0.2073	-0.1516*
Eger Superior	1.9728***	1.0134***	1.9488***	0.8084***	1.5416***	0.7459***	1.0889***	0.6447***	0.7472***	0.2604*
Eger Grand Superior	2.2992***	0.6544***	2.4390***	0.5159***	1.7119***	0.7989***	1.6607***	0.7709***	1.8716***	0.6949***
Eger before 2010	1.8648***	0.7174***	2.0819***	0.5044***	1.4674***	0.2467***	1.0130***	0.0862	0.8748***	-0.3027**
Etyek-Buda	1.0436***	0.6628***	1.2342***	0.5723***	0.4422***	0.3544***	-0.0005	0.2647***	-0.0557	-0.0429
Felső-Magyarország	0.5705***	0.4015***	0.9462***	0.3781***	0.4641***	0.2122***	0.1669*	0.1011	-0.1554	-0.1913**
Hajós-Baja	1.1008***	0.5517***	1.0527***	0.2892***	0.3208***	0.0494	-0.2374*	0.0202	-0.6130***	-0.1738
Káli	1.6456***	1.0802***	2.0823***	1.0869***	1.1984***	0.6459***	0.8620***	0.8944***	0.7612***	0.3935***
Kunság	0.9829***	0.2817**	1.0527***	0.1640**	0.3296***	-0.0329	-0.2371**	-0.145	-0.6643***	-0.3846***
Mátra	0.6965***	0.4246***	0.7637***	0.2442***	0.2804***	0.0044	-0.1725**	-0.1243	-0.5176***	-0.3500***
Mór	1.3813***	0.8565***	1.2342***	0.5878***	0.5113***	0.2507**	-0.2364	0.0549	-0.6125**	-0.2875*
Nagy-Somló	1.1008***	0.7352***	1.4575***	0.6803***	0.8949***	0.3831***	0.5936***	0.3964***	0.0294	0.1479
Neszmély	1.2889***	0.6438***	1.2342***	0.4259***	0.4422***	0.1208	-0.0272	0.0302	-0.5927***	-0.2766**
Pannon	1.1871***	0.6462***	1.1471***	0.5157***	0.4066***	0.2854***	-0.2431	0.1888	-0.7756***	-0.0821
Pannonhalma	1.4697***	0.9203***	1.5833***	0.7791***	0.7991***	0.5177***	0.2744**	0.4287***	-0.2137	0.0292
Pécs	1.2073***	0.7075***	1.1480***	0.4846***	0.5119***	0.1644**	-0.0005	0.07	-0.3127	-0.0404
Sopron/Ödenburg	1.5438***	0.7871***	1.4581***	0.6179***	0.7640***	0.3075***	0.6109***	0.1395	0.3138*	-0.1395
Szekszárd	1.2063***	0.6653***	1.4311***	0.5095***	0.7430***	0.2994***	0.3551***	0.2011***	0.0804	-0.1108
Tokaj wine speciality	2.0822***	1.0335***	2.4551***	0.8068***	2.1815***	0.5661***	2.1615***	0.5117***	2.1702***	0.2569***
Tokaj non-wine speciality	1.2063***	0.5342***	1.3892***	0.4472***	0.9394***	0.2857***	0.7319***	0.4184***	0.6194***	0.2474***
Tolna	0.6319***	0.2414	1.0426***	0.1854*	0.4780***	0.0121	-0.1533	-0.0147	-0.2513	-0.3289***
Villány Classicus	1.1008***	0.6348***	1.3143***	0.4954***	0.5759***	0.2760***	0.1461*	0.1831**	-0.2104	-0.1427*
Villány Pérmium	2.1434***	1.1973***	2.2252***	0.9512***	1.7119***	0.7201***	1.3446***	0.6750***	0.9960***	0.3876***
Zala	1.2063***	0.5899***	1.3143***	0.2598	0.5759***	0.032	0.0672	-0.2654	-0.4385**	-0.5653***
Constant	5.7004***	8.1203***	5.8551***	8.2918***	6.8013***	8.6511***	7.5496***	8.8891***	8.2134***	9.0275***
Pseudo-R^2	0.3261	0.5316	0.2655	0.4970	0.2262	0.4861	0.2573	0.5173	0.3127	0.5621
VIF	1.00	2.63	1.00	2.63	1.00	2.63	1.00	2.63	1.00	2.63

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

The results of these models were in line with hypothesises H1.1-H1.5, and partially H1.6 as well. The models showed a positive price premium for 7-31 geographical indications out of the 33 observed (which is in line with H1.1). Besides, the value of the price premium was negative for 0-13 GIs depending on the model specification. The results are in line with that of models A2-A6 as they show that the price premia of GIs are generally and gradually decreasing moving towards higher price segments (31, 30, 24, 16 and 7 GIs for percentiles 10, 25, 50, 75 and 90) and then "run out" for most GIs. The number of the premia turning into negative is increasing in the case of these models, too (0, 1, 1, 1 and 13 GIs for percentiles 10, 25, 50, 75 and 90).

The seven GIs with positive coefficients at the highest price segment were Bükk, Káli, Eger Superior, Eger Grand Superior, Villány Prémium, Tokaj wine speciality and Tokaj non-wine speciality. In the restricted models, the highest price segment contained nine GIs with a positive coefficient: Badacsony, Eger Superior, Eger Grand Superior, Eger before 2010, Káli, Sopron/Ödenburg, Tokaj wine speciality, Tokaj non-wine speciality and Villány Prémium. Similar to models A2-A6, the addition of all variables resulted in PDO Bükk replacing PDO Sopron/Ödenburg at the ninth decile in the group of GIs with a positive price premium. Moreover, similarly to previous models, in most cases, the GI-coefficient estimated by the restricted model decreased in the extended model.

In the medium segment (at the median), Eger Grand Superior has the highest premium (+122%). High price premia were estimated for Eger Superior (+111%), Villány Prémium (+105%), Káli (+91%), Tokaj wine speciality (+76%) and Pannonhalma (+68%).

The price of single-vineyard wines is 87-62% higher than other wines (the lowest value was estimated for the third quartile, and the highest for the ninth decile).

This approach confirmed that prices had a strong and robust relationship with individual brands (complying with H1.2; +43-51% for the 1st tier and +31-38% for the 2nd tier). The premium of Tier1 was the highest at the two ends of the market, similarly to models A2-A6. These estimated coefficients are considerably lower by (4-51 and 14 to 103 percentage points, respectively) than those estimated by restricted models (No. 2R2-6R2). Thus, the expected order of the estimated coefficients of Tier1 and Tier2 individual brands has been restored in these extended models and in all quartiles, too.

As H1.3 suggested, the sugar-free extract is positively related to the price, while the sugar content has a controversial impact on white and non-white wines. An additional gram of the sugar-free extract would cost more and more as the price increases (0.3, 0.5, 0.8, 0.9 and 0.6% for percentiles 10, 25, 50, 75 and 90). The extent of the impact is cut by 5-13 compared to the estimations of the restricted models. The positive impact of an additional gram of sugar content on white wine prices is relatively small and has a U-shape with the growth of the price (0.39% at both ends and 0.28% at the median). Meanwhile, the negative impact of an additional gram of sugar on rosés and reds grows along with the price (the absolute value increases from 0.34% in the first decile to 0.90% in the third quartile and then decreases to 0.85% in the ninth decile). The relevant restricted models estimated a statistically insignificant impact of sugar content on white wine prices. However, the negative effect on rosé and red prices was estimated 3 to 10 times larger by the relevant restricted models.

Older wines cost more (H1.4), the impact of an additional year of ageing is 8-17% and grows with the increase of the price. This impact has decreased by 11 to 18 percentage points compared to the relevant restricted models.

The relation of the lot size and the price is negative (H1.5), with 1% of the increase in quantity the prices decrease by 0.18-0.23% (a monotonously decreasing impact with the growth of the price). This impact decreased by 8 to 17 percentage points compared to the relevant restricted models.

The hypothesis on the role of colour and varieties (H1.6) was not confirmed unambiguously. The expected positive price premium for red wines was only present in case of Bordeaux varietals and only for the third quartile and the ninth decile. Other red categories were estimated to have a negative price premium in all quantiles except for the third quartile and the ninth decile (and the first decile for reds without varietal information). The situation was similar for the white wines as well, albeit the models estimated statistically significant and negative coefficients for Cserszegi or Irsai in two quantiles. The estimated coefficients for the variables reflecting colour and varietals were considerably higher in all relevant restricted model (except for Cserszegi or Irsai). This suggests that in the reality, some other factors explain the differences in wine prices that seemed to be caused by varietal composition.

The explanatory value of the models increases by the inclusion of new variables, with the value of pseudo-R^2 increases to 0.4808-0.5561 (slightly higher than those of models A2.7-A6.7). Therefore, the final extended model explains about half of the variance of the prices.

4.1.6 Comparison of approaches "A" and "B"

Regardless of the actual model specification, the results of the first step confirmed all hypothesises (although it is just partially true for hypothesis H1.7 on colour and varietals).

Table 37

The market position of the geographical indications

Description of the group	Models type "A"	Models type "B"
The price premium is positive in all segments	Káli, Tokaj	Eger Grand Superior, Eger Superior, Káli, Tokaj non-wine speciality, Tokaj wine speciality, Villány Prémium
The price premium is positive in all segments except for the high end	Badacsony, Balaton, Balatonboglár, Balatonfüred-Csopak, Eger, Etyek-Buda, Nagy-Somló, Pannon, Pannonhalma, Szekszárd, Villány	Badacsony, Balaton, Balatonboglár, Balatonfüred-Csopak, Etyek-Buda, Nagy-Somló, Pannonhalma, Szekszárd
The price premium is positive in the lowest and middle segments, and is not negative in other segments	Pécs, Sopron/Ödenburg	Balaton-felvidék, Pannon, Pécs, Sopron/Ödenburg
The price premium is positive in the lowest and middle segments, but turns to negative in one of the higher segments	Felső-Magyarország	Eger Classicus, Eger before 2010, Felső-Magyarország, Mór, Villány Classicus
The price premium is positive in the lowest segments, but is not significant in all of the other segments	Balaton-felvidék, Bükk, Hajós-Baja, Mór	Bükk, Hajós-Baja
The price premium is positive in the lowest segments, statistically not significant in the middle segment and turns to negative in one of the higher segments	Dunántúl, Kunság, Mátra, Neszmély, Zala	Duna, Dunántúl, Kunság, Mátra, Neszmély
The price premium is positive only in the low end, and turns to negative in one of the higher segments	Duna	Tolna, Zala
The price premium is not positive in any segment.	Duna-Tisza közi, Tolna	Duna-Tisza közi

Source: Own composition

The results underline that in general, geographical indications may impact wine prices; however, this is not true for all of them and the impact may be negative as well. On the other hand, negative coefficients show that some geographical indications are positioned low, which might be a joint and conscious action of the producers. The group of GIs with positive coefficients in all segments mainly include the most known ones with somewhat larger production and well-organised producers' group or small ones with unique wine character.

Table 37 summarises and compares the results of models type A (models A2.7-A6.7) and B (models B2.7-B6.7) regarding the sign of the coefficient of the GI dummies and groups them according to their market position.

As expected, the explanatory value of extended models using approach B (considering GIs with several quality levels separate ones) slightly exceeded those using approach A in most cases.

4.1.7 Analysis of the estimated GI price premia[10]

Hereby I analyse the estimated price premia for each GI including the comparison of the restricted and extended models and the different market segments. The addition of new variables to the restricted models show different reasons of the decrease of the value, or even losing the statistical significance of the GI coefficient in each case. The comparison of the estimated price premia at the different market segments reflect the actual positioning of the GIs. As a benchmark, the mean and median of the estimated price premia of models A1.7 and B1.7 are presented in Table 38.

Table 38

The mean and the median of price premia estimated by models A1.7 and B1.7

Model	A1.7	B1.7
Mean of estimated price premia	24%	31%
Median of estimated price premia	31%	31%

Source: Own calculations

[10] This section considers only those estimated coefficients that have a statistical significance at significance level a=0.5.

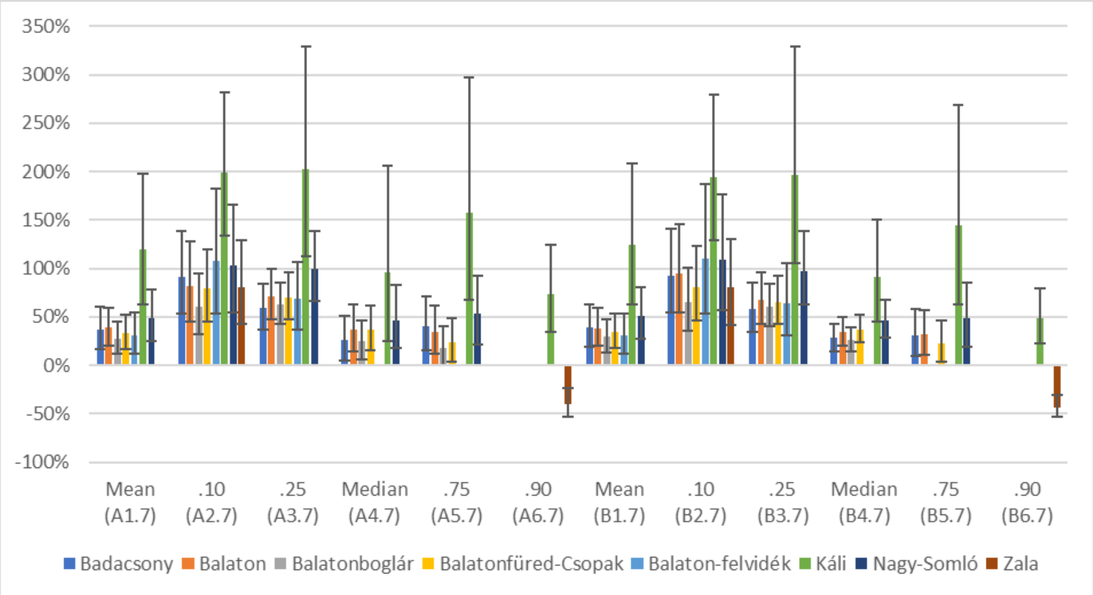
4.1.7.1 Balaton region

Figure 11 shows the estimated price premia of GIs from the Balaton region

Badacsony starts quite high at lower segments, and then its coefficient loses its significance at the top end (ninth decile). The estimated price premia slightly exceed the average and the median. The addition of new variables to the restricted models results in a constant decrease in the estimated price premium.

Figure 11

The estimated price premia of GIs of the Balaton region



Source: Own calculations

The regional GI, Balaton shows solid price premia in all but the highest segment where its coefficient loses its statistical significance. The steps from the restricted towards the most extended models show the volatility of the estimated price premium. Hence, wines with the GI Balaton tend to have lower values of sugar and sugar-free extract than the average and tend to be sold young. The price premia estimated by models A1.7 and B1.7 exceed the average and median.

The price premium of Balatonboglár interestingly shows some increase from the low end to the middle-low segment; however, its coefficient loses its statistical significance already at the middle-high segment (third quartile). The inclusion of nearly all variables lowers the estimated price premium except for the age, meaning that these bottles are sold relatively young. The estimated premia at the average roughly equal to the mean and median price premia.

Balatonfüred-Csopak's price premium starts a steady decrease after the middle-low segment and loses the statistical significance for the high end. The addition of new variables to the extended model lowers the estimated price premium, except for the age, which means that these wines sell at a younger age. The price premia estimated by models A1.7 and B1.7 slightly exceed the average and median.

Balaton-felvidék shows a substantial positive price premium at the average. However, the estimations using quantile regression models are ambiguous whether its coefficient is significant statistically at the median or not. Both approaches show that the price premium cannot be distinguished from zero at higher segments (the third quarter and the ninth decile). The enlargement of the model specification brings lower estimations of price premium here, too, with the addition of the age also being an exemption. The estimated premia at the average roughly equal to the mean and median price premia.

Káli is one of the highest-ranking GIs in the whole country according to my estimations. The estimated price premium is over 100%, obviously significantly exceeds both the average and the median premia (both at the average) and is positive in all segments. The price premium estimated by the restricted model shows a steady decrease with the inclusion of new variables, with an exemption, which is, however, not at the age, but individual brands as Tier1 and Tier2 does not contain any producer of wines with this GI[11].

Nagy-Somló is a small GI with a positive and rather high price premium, which is around 100% in the lower segments, then slightly under 50% in the middle of the market and decreases to 0 for the high end. The price premia estimated by models A1.7 and B1.7 considerably exceed the national average and median. The addition of new variables to the models results in the decline of the estimated price premium (except for vineyard names, which is due to the uncommon practice of labelling them on Nagy-Somló wines).

The price premium of Zala starts at a positive value in the low end then shrinks to zero for the middle segments then turns negative for the high end. During the bottom-up model design, the coefficient of Zala lost its significance after the inclusion of

[11] Note that this has changed since the time of the collection of data.

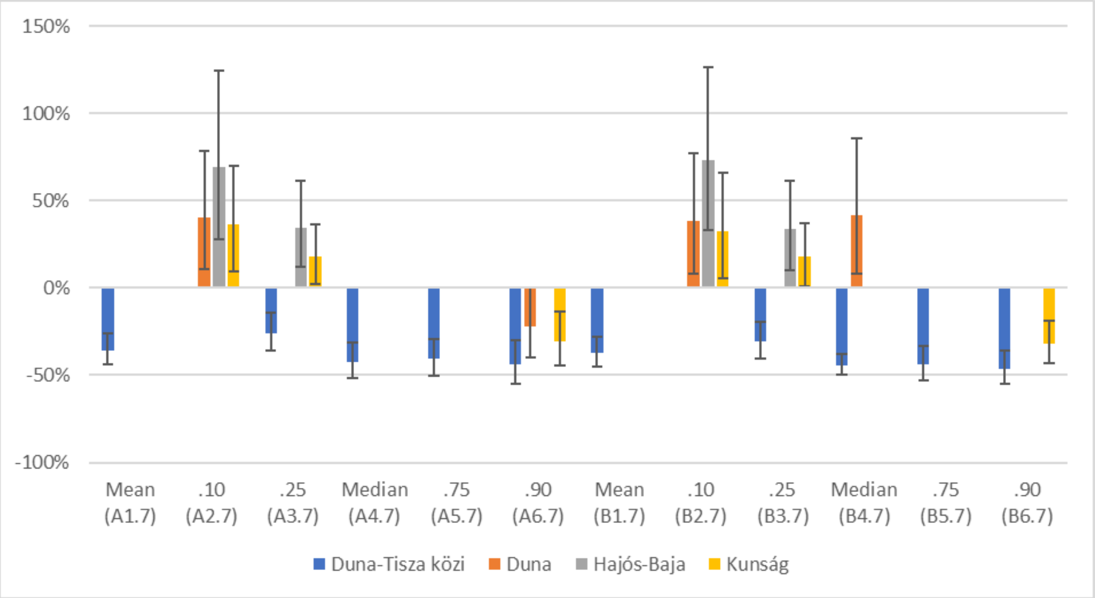
individual brands. However, the addition of age turned the price premium significantly positive, which was lost after adding lot size. This means that Zala wines are sold in rather small batch sizes at a young age. The impact of individual brands suggests that premium brand(s) play a considerable role in the market presence of Zala wines in the off-trade sector.

4.1.7.2 Duna region

Figure 12 shows the estimated price premia of GIs from Duna wine region.

Figure 12

The estimated price premia of GIs of the Duna region



Source: Own calculations

Duna, the regional PDO is estimated to have a positive coefficient at the low end both by models A2.7 and B2.7, which decreases to zero in both models for the first quartile, the median and the third quartile and turns into negative in the high end.

Duna-Tisza közi seems to be the PGI for the cheap wines of the region as its estimated coefficient is always negative except for the first decile, where it is not statistically significant.

Hajós-Baja starts from a relatively high price premium at the low end, which remains positive at the first quartile, and then reduces to zero starting from the median. Interestingly, the price premia estimated by the restricted models are significant and negative in the highest segments. This suggests negative impact may be caused by the relatively young age and large lots in Hajós-Baja wines are sold.

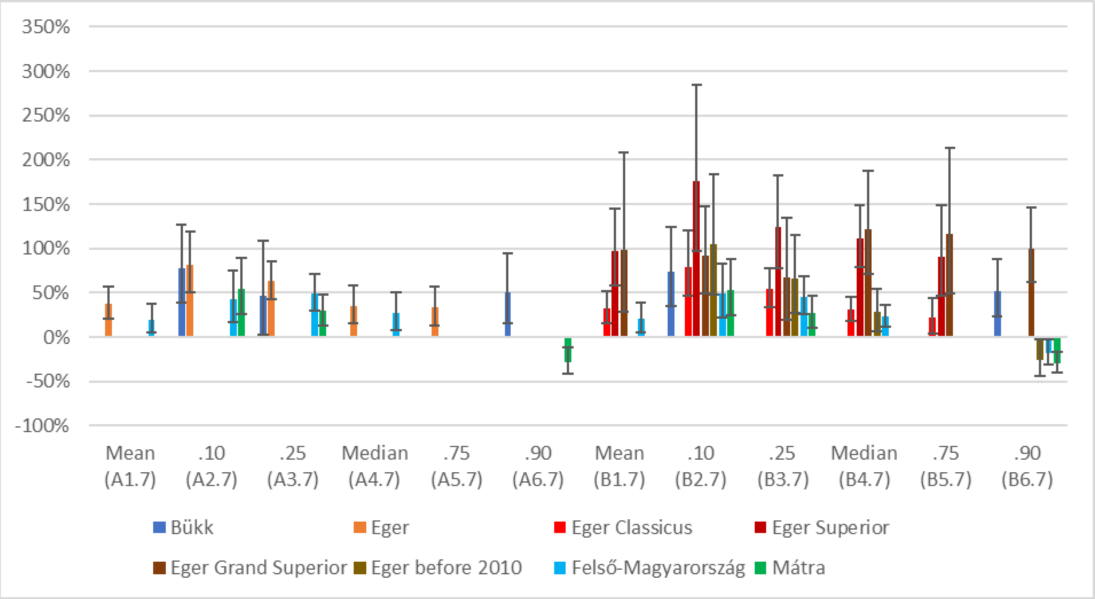
Kunság has solid estimated price premia in the lowest segments, which turns to zero for the median, and then into negative for the highest segment (even in the restricted models).

4.1.7.3 <u>Felső-Magyarország region</u>

Figure 13 shows the estimated price premia of GIs from Felső-Magyarország wine region.

Figure 13

The estimated price premia of GIs of the Felső-Magyarország region



Source: Own calculations

The regional GI, Felső-Magyarország, has positive estimated price premia in the lower and middle segments. It remains below the average and median, but interestingly, exceeds the price premia of Mátra and Bükk and does not differ significantly from that of Eger and Eger Classicus.

Bükk is a relatively small GI, with solid estimated price premia in the lowest segments and surprisingly in the high end. Meanwhile, the estimated price premium is not significant in extended models for the median, the average and the third quartile. Comparing the restricted and the extended models reveal that the coefficient of the Bükk dummy turns only to zero in these cases with the inclusion of lot size, therefore, the relatively higher prices of Bükk wines in the Hungarian off-trade sector are mainly due to their small amount.

The coefficients of the Mátra dummy decline consistently over the emerging price segments, even turning to negative in the end. Therefore, the estimated price premium of Mátra is positive in the two lowest segments, zero in the median and the average, and negative in the high end in both types of models. However, for the third quartile, model A5.7 estimates a price premium which is not significant statistically, while the estimation of model B5.7 is negative. Comparison of restricted and extended models show a notable decline of the estimated coefficient with the inclusion of chemical composition, age and lot size.

Eger is one of the PDOs with several (3) quality tiers. A major reform of the rules on the use of the PDO Eger took effect from the 2010 harvest, including the introduction of several (first two and then three) classification levels (previously existing only for the Egri Bikavér wines). At the time of the data collection, there were still some wines on the market from previous vintages; obviously in the higher segments (typically aged red wines of first or second-tier wineries, which would probably have been classified into the Eger Superior or Eger Grand Superior categories, if they existed then). Therefore, it was justified to create a separate category for them in the context of the present analysis. Moreover, the evaluation of these wines does not allow a valid conclusion on the general market positioning of pre-2010 wines bearing the PDO Eger.

The results of the models that consider PDO Eger as a sole GI show a substantial price premium that declines consistently over the price segments and loses its statistical significance in the high end. The price premia estimated by model A1.7 exceeds the national average and median. The comparison of restricted and extended models shows a steady decline in the price premium with the inclusion of additional variables. Only the addition of lot size raises the estimated coefficient suggesting that Eger wines are generally sold in large lots.

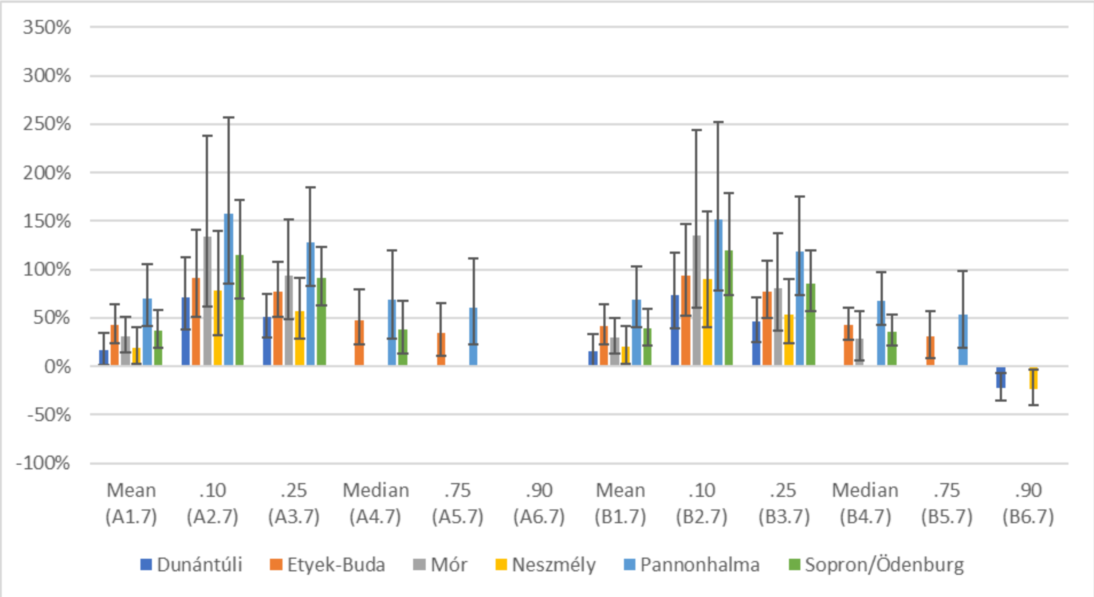
Decomposing the PDO into quality tiers reveals the full picture. Eger Classicus has a high price premium in the lowest segment steadily declining and turning into zero in the high end. Eger Superior starts with a very high premium that declines but remains positive in all segments. Eger Grand Superior, however, has a smaller premium in the lower segments, only surpassing Eger Superior in the median and the higher segments. Comparing the estimations for the average, we cannot observe a significant difference between the premium for Eger Superior and Grand Superior. However, in higher segments, the difference arises and becomes statistically significant. The results show that Eger wines before 2010 have a declining estimated premium over the market segments which is statistically not significant at the mean and turns to negative in the highest segment. Thus, the relatively high price of these wines is due to their higher mean age, their red colour and their varietal composition.

4.1.7.4 Felső-Pannon region

Figure 14 shows the estimated price premia of GIs from Felső-Pannon wine region.

Figure 14

The estimated price premia of GIs of the Felső-Pannon region



Source: Own calculations

Dunántúli is a PGI with a production area covering three wine regions in the Transdanubia region of Hungary. Although its big size and low standards, the estimated price premium at the average is 15-16% (considerably lower than the mean and median price premium estimated by models A1.7 and B1.7). Dunántúli is the only GI that has a statistically non-significant estimated price premium in the restricted (robust standard error) models, and the most extended models estimate a statistically significant and positive price premium. Comparing the results of models A1.1-7 and B1.1-7 suggests that this may be since these wines are sold in large lots. The quantile regression models estimate a positive price premium for Dunántúli in the two lowest segments. However, this shrinks to zero and remains there for the median and the higher segments.

All models except for A6.7 and B6.7 (for the ninth decile) estimate a statistically significant positive price premium for Etyek-Buda. The price premium declines as we investigate higher and higher segments. The premia at the mean (models A1.7 and B1.7) are higher than the average and the median price premium estimated by these models.

Mór is one of the GIs, where the estimation of models A4.7 and B4.7 for the median differ: the latter estimates a non-significant impact of this GI at the middle price segment. The two approaches have the same results in the lower and the higher segments and for the mean: the price premia starts very high (120-121% for the first decile) and gradually decreases to zero, with a 30-31% price premium for the average (which more or less equals to the average and the median premium).

Neszmély shows a similar pattern; however, model B6.7 estimates a negative price premium for this GI at the ninth decile. The premia at the mean (models A1.7 and B1.7) are appreciably lower than the average and the median price premium estimated by these models.

Pannonhalma's estimated price premia start at very high levels in lower price segments, shows a solid (+69-70%) premium at the median and the mean and decrease to zero for the ninth decile. The premia at the mean (models A1.7 and B1.7) are considerably higher than the national average and median price premia.

Sopron/Ödenburg shows high estimated price premia for the first two price segments and the mean. The estimated premia at the mean (models A1.7 and B1.7) are somewhat higher than the national average and median. However, the models for the third quartile and the ninth decile estimate a statistically non-significant price premium.

4.1.7.5 Pannon region

Figure 15 shows the estimated price premia of GIs from Pannon wine region.

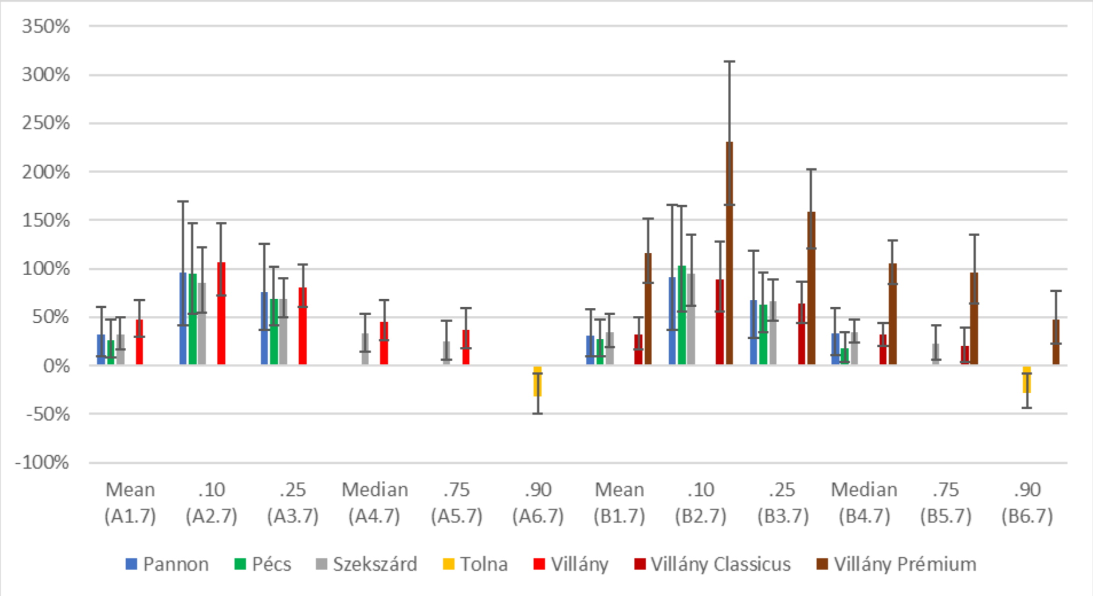
Pannon is the regional PDO for Pannon wine region. Estimates show a solid price premium for the mean the median. The premia at the mean are slightly higher than the national average and median in case of model A1.7 and equal to them in case of model

B1.7. Price premia for the lowest segments are relatively high, while they decrease to zero for the third quartile and the ninth decile.

Pécs shows a smaller yet positive premium for the average. The premium at the mean is slightly higher in case of model A1.7 and slightly lower in the case on model B1.7 than the mean estimated price premium, and lightly lower than the median price premium in both cases. It fits into the general pattern of statistically non-significant premia at the higher segments. Models A4.7 and B4.7 are ambiguous if the decline to zero starts at the median or higher segments.

Figure 15

The estimated price premia of GIs of the Pannon region



Source: Own calculations

In the case of Szekszárd, the estimated price premia unambiguously remain positive until the ninth decile. The premia at the mean (models A1.7 and B1.7) are slightly higher than the national average and median.

The estimated price premia of Tolna show an interesting pattern as they are statistically significant only for the ninth decile (both in models A6.7 and B6.7), with a negative value.

Villány is one of the GIs with several quality tiers. With the creation of Super Prémium, the number of regulated quality levels has become three since the 2014 harvest. However, due to the harvest conditions then and the required ageing time, Villány Super Premium wines were not available on the market at the time of the data collection. Therefore, only two tiers, Villány Classicus and Villány Prémium were taken into account.

If Villány is treated as one GI, its estimated price premia are positive, yet decrease gradually to zero for the ninth decile. However, the price premium at the mean (model A1.7) is considerably higher than the national average and median.

The estimated price premia of Villány Classicus show a very similar pattern to that of Villány, albeit they are 10-15 percentage point lower. The price premium at the mean is close (+1%) to the national average and median price premium estimated by model B1.7.

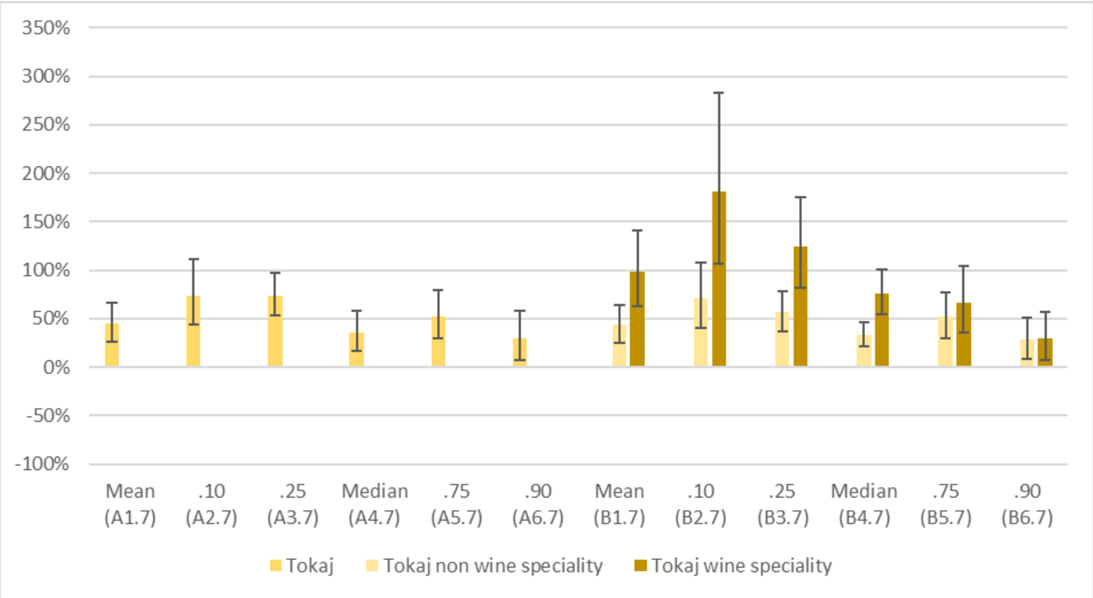
Villány Prémium shows substantially and significantly higher price premia than Villány Classicus. Although the premium is decreasing as the price segment augments, it stays positive (and high) even in the ninth decile.

4.1.7.6 Tokaj region

Tokaj is the most famous Hungarian GI and one of those that can be split into several quality tiers. Here, the tradition serves as the basis of the division. Tokaj wine specialities constitute one tier, and Tokaj non-wine specialities form the other. Figure 16 shows the estimated price premia of the PDO Tokaj.

Figure 16

The estimated price premia of the PDO Tokaj



Source: Own calculations

When treated as a sole GI, the price premia of Tokaj are positive and statistically significant in all segments. Additionally, the premium at the average is considerably higher than both the mean and the median of the price premia estimated by model A1.7.

Tokaj wine specialities have very high estimated price premia in the lower segments, which decreases to 29% at the high end. At the mean (model B1.7), the estimated premium is vastly higher than both the national average and median. The study of the restricted and extended models shows that the price premium (at the mean) starts at 863% and gradually decreases as more and more factors are added to the model. The largest drop of the estimated coefficient occurs with the inclusion of variables describing chemical composition (as these wines are very rich in compounds).

The price premia of Tokaj non-wine specialities is significantly lower than that of wine specialities but is still positive and statistically significant in all price segments; however, the premium estimated at the mean somewhat exceeds the national average and median. The decrease of the coefficient of the Tokaj non-wine speciality dummy between models B1.R1 and B1.2 reflects the importance of single-vineyard Tokaj wines.

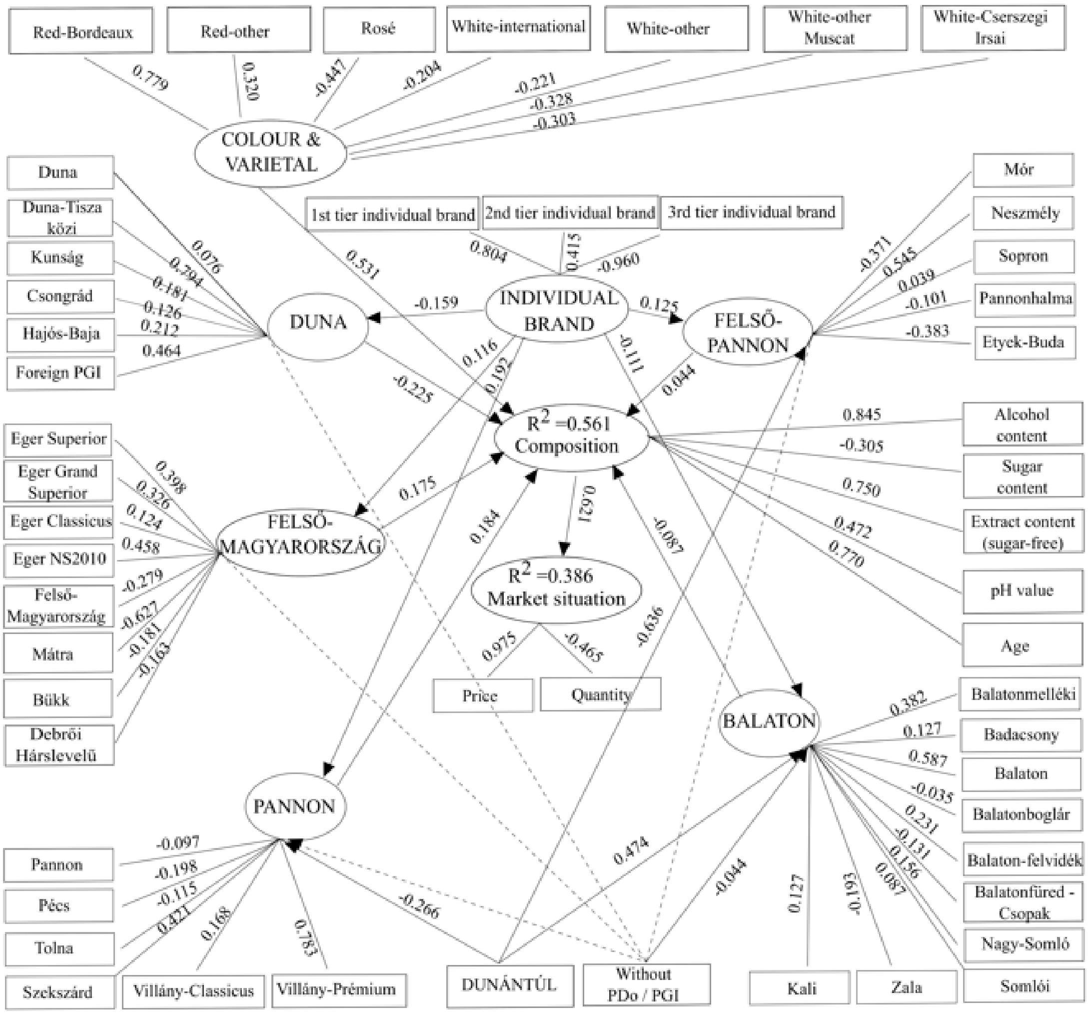
4.1.8 The results of the LVPLS model

The composite reliability of the blocks was tested by the explained variance. For estimating the initial weights in the model, the Centroid Scheme was used. The PLS algorithm stopped when the change in the outer weights between two consecutive iterations was smaller than 0.0001 or the number of iterations reached 100. Bootstrap sampling was also applied for model testing and parameter estimation in which 500 samples were generated from the original data as suggested by Chin (1998). This means that the mean and standard error of the parameters were computed from the total number of samples and only those path coefficients were considered statistically significant that were at least twice their respective standard error. A normalised version of the Goodness-of-fit (GoF) as proposed by Esposito Vinzi et al. (2010) was used to measure the overall model fit by obtaining bootstrap resampling. The GoF of 0.10, 0.25, and 0.36 can be considered an adequate, moderate and good global fit, respectively (Wetzels et al., 2009). During inner model quality assessment, R^2 measures were calculated. The R^2 values of 0.02;0.15;0.35 are considered as small, medium or large effects according to Cohen (1988). In order to assess the discriminant validity of the model, the Fornell and Larcker (1981) criterion was applied.

Figure 17 provides a graphical representation of the parameter estimates in the model. Path modelling groups GIs into blocks according to the *regional origin* they belong to and then examines the paths and links between *regional origins* and *composition, colour and varietal*, *individual brands* in terms of regression coefficients. The model is exploratory, and the algorithm is iterative, hence able to identify irrelevant connections. Ovals represent the LVs (blocks), and rectangles stand for the MVs. All the links (arrows) are significant at 5% level, while the dotted lines represent non-significant links.

Figure 17

Path model and path coefficient estimates from the bootstrapping



Source: Own calculations

Based on the result of the bootstrap analysis, the regression coefficients between the LVs were proved valid (the standard errors of the regression coefficients will be provided for verification). Regarding the goodness of fit, the GoF of the inner model was 0.770, the GoF value of the outer model was 0.958 and the entire model has a GoF of 0.738, which shows an excellent fit. The two main regressions of the model are (1) *composition* (R^2=0.561) regressed by the *regional origins* and *colour and varietal* and (2) *market situation* (R^2=0.386) regressed by *composition*. The proportion of variance explained in the two regressions is appropriate.

In the latter case, the regression coefficient of *composition* was 0.621 (t=38.1; p<0.001, SE=0.016) with regards to *market situation*.

All manifest variables of *composition* are in a significant relation with it, and their effect is positive except for sugar content. That means that the more concentrated a bottle of wine is, the higher its price and the lower its quantity will be, while wines (originating outside of Tokaj wine region) with higher sugar content are cheaper and produced in larger batches. This confirms hypothesis H1.3 and the results of regression models.

The effect of regional origins largely depends on the actual region. Felső-Magyarország (ß=0.175; t=12.6; p<0.001, SE=0.014), Felső-Pannon (ß=0.044; t=3.0; p<0.001, SE=0.015) and Pannon wine regions (ß=0.184; t=11.7; p<0.001, SE=0.015) affect *composition* positively, while the effect of Balaton (ß=-0.087; t=-5.8; p<0.001, SE=0.015) and Duna (ß=-0.225; t=-15.9; p<0.001, SE=0.014) regions is negative. This means that wines from Felső-Magyarország, Felső-Pannon and Pannon regions are sold at higher prices, in smaller batch sizes and have higher intrinsic value (*composition*). On the contrary, wines from Balaton and Duna region wines have lower prices, higher quantity and lower intrinsic value (*composition*).

Collective or individual brands may alter the effects of regional origin. Higher tier individual brands (Tier1 and Tier2) always positively affect *composition* and compensate potential negative regional effects. The effect of using a Tier1 brand is double to that of a Tier2 brand. The findings confirm hypothesis H1.2 and are in line with those of the regression models.

Meanwhile, the role of GIs is versatile; however, all of them were significant. In regions, where the regional origin is positively related to *composition* (Felső-

Magyarország, Felső-Pannon and Pannon), only half of the GIs strengthen this effect. The different classes of Eger (Eger Classicus [0.124], Eger Superior [0.398], Eger Grand Superior [0.326] and Eger before 2010[0.458]) have a positive effect. On the other hand, Mátra (-0.627), Bükk (-0.181), Debrői Hárslevelű (-0.163) and Felső-Magyarország (-0.279) have a negative impact. Considering the GIs of the Felső-Pannon region, the effect of Neszmény (0.545) and Sopron/Ödenburg (0.039) is positive, while that of Etyek-Buda (-0.383), Mór (-0.371) and Pannonhalma (-0.101) is negative. However, the relatively small coefficient of the regional reputation (0.044) considerably limits these impacts. In Pannon region, only Szekszárd (0.421) and the two tiers of Villány (V.Classicus: 0.168 and V.Prémium: 0.783) have a positive effect, while Pannon (-0.097), Pécs (-0.198) and Tolna (-0.115) have a slightly negative effect. A higher negative effect can be found for Dunántúl (-0.266). Both in the case of Eger and Villány, the effect of top categories (E.Superior and E.Grand Superior, V.Prémium) significantly exceeds the effect of low categories (E.Classicus and V.Classicus).

There are two regions, where regional origin yields a negative effect: Balaton and Duna. Only 3 out of the 16 concerned GI has an impact that changes the negative coefficient of the regional origin into positive: Balatonboglár (-0.035), Balatonfüred-Csopak (-0.131) and Zala (-0.193). All other GIs keep the negative effect of regional origin on *composition*. The highest impact is of Duna-Tisza közi (0.794), imported PGIs (0.464), Balaton (0.587), Balatonmelléki (0.382). Also, PGI Dunántúl has an overall negative effect on *composition*, regardless of their regional origin. Not using a GI affects only the Balaton regional origin, slightly moderating its negative impact (-0.044).

Comparing these results with that of regression models B1.7 (for the average) and B4.7 (for the median), we can find that the estimated impact of GIs on the price using LVPLS is lower. In case of eleven (eight) GIs having a positive estimated coefficient by model B1.7 (B4.7), the LVPLS model revealed a negative effect on the price. Moreover, there is one (four) GI dummy that does not have a significant impact on prices according to model B1.7 (B4.7), are estimated to affect the *market situation* in a negative manner by the LVPLS model. In spite of these contradictions, H1.1 (that not GIs have a positive impact on the price) can still be considered confirmed by the LVPLS, with the remark that this method seems to estimate the effect of GIs at a lower level and that this method measures the indirect impact of prices on a LV that includes prices and lot size.

The explained deviation is presented in the main diagonal of the correlation matrix (Table 39) and shows how much a LV explains from its MVs. The figures under the main diagonal are the Pearson correlations between the LVs. The values above the main diagonal show the significance of the Pearson correlation coefficients. It is obvious that each LV explains at least an average of 30% of the deviation of all the items linked to it and the model does not conflict the Fornell and Larcker criterion (therefore, each LV is more related to its MVs than to any other LVs). The highest correlations can be seen between *composition* and *market situation* (r=0.603), and between *composition*/*market situation* and regions Pannon (r=0.407;0.355) and Duna (r=-0.380;-0.310).

Table 39

Pearson correlations between latent variables and standard deviations

Latent variable	1	2	3	4	5	6	7	8
Individual brand (1)	**0.760**	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Duna (2)	-0.156	**0.398**	0.943	0.834	0.017	<0.001	<0.001	<0.001
Felső-Magyarország (3)	0.114	-0.002	**0.358**	0.238	0.967	0.895	<0.001	<0.001
Felső-Pannon (4)	0.172	-0.004	-0.001	**0.412**	<0.001	0.082	<0.001	0.001
Balaton (5)	-0.118	-0.050	-0.001	-0.243	**0.303**	<0.001	<0.001	<0.001
Pannon (6)	0.190	-0.157	-0.003	0.036	-0.134	**0.355**	<0.001	<0.001
Composition (7)	0.216	*-0.380*	0.208	0.071	-0.174	*0.407*	**0.600**	<0.001
Market situation (8)	0.265	*-0.310*	0.199	0.065	-0.112	*0.355*	*0.603*	**0.781**

Source: Own composition

4.1.9 Comparison of the results of the first step and the literature

The results of the first step concerning GIs are in line with the findings of the international literature. However, in general, we cannot consider GIs the most important price-determining element of the wine market in Hungary (unlike Span [Angulo et al., 2000] and Sicily [Di Vita et al., 2015]). The findings are consistent with previous results concerning the regional hierarchy of GIs (Ali and Nauges, 2007; Blair et al., 2017; and Combris et al., 2000) and smaller geographical units (San Martin et al., 2008).

The results regarding the role of individual brands of studies are in line with those of research conducted abroad (Frick and Simmons, 2013; Masset el et al., 2016; Haeger and Storchmann, 2006; Oczkowski, 2001; Oczkowski, 2016; Roma et al., 2013; San Martín et al., 2008; Shane et al., 2018; Viana and Rodriguez, 2007): the price increases with the improvement of individual reputation.

The positive relationship between the price of wines and the concentration of their chemical compounds has been demonstrated in the literature to date using the actual alcohol content (Arancibia et al., 2015; Roma et al., 2013; Levaggi and Brentari, 2014 and Thrane, 2009). The results confirmed the same relation using the sugar-free extract content (which is harder to obtain) instead of the actual alcohol content.

The negative relationship between price and quantity is consistent with the findings of Kwong et al. (2017, the Canadian market) and San Martín et al. (2008, the market of the United States).

4.2 Second step

Given their policy relevance, the second step aims to reveal the factors influencing the market value of geographical indications.

4.2.1 Restricted models

Due to the methodological difficulties detailed in section 3.4.2, the results of the restricted models regarding the hypothesises of the second step are presented in detail, too (Table 40 and 41). All restricted models confirmed hypothesises H2.1-H2.4.

The rigour of production rules has a positive impact on market value in all models. The mean price of a GI where an additional hl of wine is allowed to be produced on one hectare is 2.81-2.97% lower, while the impact on implicit prices is a decrease of 1.42 to 1.68 points.

Group heterogeneity is strongly connected to the market value of GIs. The mean price of wines using a GI belonging to a producer group with an additional hl to the average of the standard deviation in the GI use is lower by 0.76% to 0.92%, and the implicit prices are smaller by 0.34 to 0.51 points than the average.

Table 40

Results of restricted models regarding the hypothesises of the second step (models treating GIs with several quality tiers as a sole GI)

Dependent variable	Mean price (log)	Estimated implicit price (model A1.7)	Estimated implicit price (model A4.7)	Mean price (log)	Estimated implicit price (model A1.7)	Estimated implicit price (model A4.7)	Mean price (log)	Estimated implicit price (model A1.7)	Estimated implicit price (model A4.7)	Mean price (log)	Estimated implicit price (model A1.7)	Estimated implicit price (model A4.7)
Maximum yield	-0.0297***	-1.6842**	-1.4242**									
Group heterogeneity				-0.0076***	-0.3606**	-0.3426**						
Land quality							0.0070***	0.4591***	0.3842***			
Barrier to entry										0.0258***	1.2342**	1.1907***
Constant	10.5760***	296.3748***	269.4204***	7.6862***	134.0618***	128.2542***	5.4417***	-10.0021	6.8842	6.9947***	101.0720***	96.5288***
N	28	28	28	28	28	28	28	28	28	28	28	28
R^2	0.2717	0.2097	0.1734	0.3611	0.2023	0.1982	0.2864	0.3037	0.2308	0.4030	0.2282	0.2305
AIC	28.6321	263.3413	262.3163	24.9658	263.6003	261.4629	28.0596	259.7948	260.2991	23.0671	262.6766	260.3133
BIC	31.2965	266.0057	264.9807	27.6302	266.2647	264.1273	30.7240	262.4592	262.9635	25.7315	265.3410	262.9777

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

Table 41

Results of restricted models regarding the hypothesises of the second step (models treating GIs with several quality tiers as separate GIs)

Dependent variable	Mean price (log)	Estimated implicit price (model B1.7)	Estimated implicit price (model B4.7)	Mean price (log)	Estimated implicit price (model B1.7)	Estimated implicit price (model B4.7)	Mean price (log)	Estimated implicit price (model B1.7)	Estimated implicit price (model B4.7)	Mean price (log)	Estimated implicit price (model B1.7)	Estimated implicit price (model B4.7)
Maximum yield	-0.0281***											
Group heterogeneity		-1.5387***	-1.6673***	-0.0092***	-0.4936***	-0.5148***						
Land quality							0.0094***	0.5567***	0.4358**			
Barrier to entry										0.0320***	1.7207***	1.5159***
Constant	10.4138***	284.6235***	294.4509***	7.8606***	144.8713***	142.6498***	4.8523***	-32.1633	1.7332	6.9615***	96.5320***	98.6077***
N	33	33	33	33	33	33	33	33	33	33	33	33
R^2	0.5986	0.5414	0.6552	0.2331	0.2029	0.2274	0.2342	0.2480	0.1566	0.3478	0.3046	0.2436
AIC	36.6507	308.4531	298.0427	58.0143	326.6940	324.6625	57.9693	324.7716	327.5572	52.6691	322.1900	323.9627
BIC	39.6438	311.4461	301.0357	61.0074	329.6870	327.6555	60.9623	327.7646	330.5502	55.6621	325.1830	326.9558

Source: Own calculations. *: 10%; **: 5%; ***: 1% level of significance

GIs with an additional point higher average quality of the demarcated area have a mean price 0.70-0.94% higher. The impact on the estimated implicit prices is between 0.38-0.56 points.

Geographical indications with a higher barrier to entry have higher prices. A GI with an additional percentage point of land use (note, that barrier to entry is theoretically between 0 and 1) has a mean price 2.58-3.20% higher or an estimated implicit price higher by 1.19-1.72 points.

Comparing models treating GIs with several quality tiers as a sole or separate one shows that the latter estimate larger impacts.

The comparison of the R^2 values (which are higher in the models using mean price - except for land quality in models type 1) suggests that the factors considered impact other price-affecting dimensions, too, which is in line with oenological theory (i.e. lower yields result in a higher concentration of compounds).

Both Akaike and Bayesian information criteria show the fit is the best in case of models using mean price as a measure of market value. Models using implicit prices estimated by quantile regression for the median are slightly better than those by robust standard errors from this point of view.

4.2.2 The impact of group structure on GI rules

As stated in section 3.4.2, group heterogeneity and rules on yield are not assumed to be independent of each other, e.g. the maximum level of yield as a measure of the rigour of GI rules established by the community depends on the community's decision-making capacities. In order to test this assumption, the maximum yield was regressed by group heterogeneity. Table 42 shows the results of the regression analysis.

The model treating GIs with several quality tiers as one show better explanatory value and model fit.

Model (1) shows a strong relationship between the group structure and the rigour of GI rules as the model explains almost 40% of the variance of the maximum yield. The model estimates that the producer groups with a standard deviation of the use of the GI higher by 1 hectolitre set the maximum yield 0.14 hectolitres/hectare higher. Meanwhile, the explanatory value is smaller (17%) in the case of model (2), and at the same time, the estimated impact is higher as producer groups with a standard deviation higher by 1 hectolitre tend to set the maximum yield higher by 0.22 hectolitres/hectare.

Table 42

Results of the models estimating the impact of group structure on GI rules

Model	(1)	(2)
The way the model treats GIs with several quality level	As a sole GI	As separate GIs
Dependent variable	Maximum yield	Maximum yield
Group heterogeneity	0.1397***	0.2164**
Constant	99.6287***	92.7287***
N	28	33
R^2	0.3962	0.1704
AIC	183.8755	279.3185
BIC	186.5399	282.3115

Source: own calculation. *: 10%; **: 5%; ***: 1% level of significance

4.2.3 Extended models

All restricted models (Table 43) and extended models confirm the hypotheses H2.2-H2.4.

Table 43

Results of the extended models of the second step

Model	C1	C2	C3	D1	D2	D3
Dependent variable	Mean price (log)	Estimated implicit price (model A1)	Estimated implicit price (model A4)	Mean price (log)	Estimated implicit price (model B1)	Estimated implicit price (model B4)
Maximal yield	-0.0208***	-1.1655**	-1.0023*	-0.0217***	-1.1751***	-1.4217***
Land quality	0.0050***	0.8823**	0.8984**	0.0053***	0.9244***	0.6709**
Barrier to entry	0.0204***	0.3626***	0.2932**	0.0178***	0.3378***	0.2043*
Constant	7.7391***	119.4595*	117.6848	7.7751***	126.3618***	193.7080***
N	28	28	28	33	33	33
adjusted R^2	0.6777	0.4946	0.4042	0.7650	0.6993	0.7130
AIC	6.5108	251.5256	253.8527	19.7348	295.2679	292.7360
BIC	11.8396	256.8544	259.1816	25.7209	301.2539	298.7220
VIF	1.06	1.06	1.06	1.14	1.14	1.14

Source: own calculation. *: 10%; **: 5%; ***: 1% level of significance

The mean price of a GI where an additional hl of wine is allowed to be produced on one hectare is 2.08-2.17% lower (the absolute value of the impact shrunk by 0.64-0.89 percentage points compared to the restricted models), while the impact on implicit prices is a decrease of 1.00 to 1.42 points (the absolute value of the impact decreases by 0.25 to 0.52 points compared to the restricted models).

Geographical indications with an additional point higher average quality of the demarcated area have a mean price 0.50-0.53% higher (shrinking by 0.20-0.41 percentage points from the restricted models). The impact on the estimated implicit prices is between 0.67-0.92 points (an increase of 0.24-0.51 points from the restricted models).

The mean price of a GI with an additional percentage point of land use is 1.78-2.04% higher (decreasing by 0.54-1.42 percentage points compared to the restricted models). The impact of a 1-point rise of land use ratio on estimated implicit prices of GIs varies between 0.20-0.36 points (a decrease of 0.87-1.38 points compared to the restricted models).

Both Aikike and Bayesian information criteria show that models using the mean price as a measurement for market value fit better. Moreover, adjusted R^2 values show as well that these models have higher explanatory value. However, models C2-C3 and D2-D3 (and the relevant restricted ones) use a better estimation of the actual market value of GIs as the dependent variable is cleared from other possible impacts on the price (age, individual brand, chemical composition, quantity, colour and varietal composition).

The extended models show that the regulatory and territorial parameters of GIs explain 40-71% of the variance in their market value.

5 POLICY EVALUATION OF RESULTS

In this chapter, I analyse the Hungarian wine market and formulate policy proposals based on the results presented above[12].

5.1 The situation of Hungarian wine market

5.1.1 The situation in general

The results suggest that the Hungarian wine market can be divided into two segments by the supply side. Wines with a higher concentration of compounds (sugar-free extract) are made in lower quantities and sold at higher prices. At the other end of the market, larger batches are produced of wines with low concentration of compounds and sold at a lower price. Given higher sugar levels are typically a result of sweetening in rosés and reds rather than the use of overripe grapes (which is more typical to whites, especially Tokaj wines) whose must does not ferment completely. Thus, the ambiguous relationship of sugar content and price is entirely in line with theory suggesting that homogenous wines shall be produced in large quantities and sold at an average price.

The models also suggest that wines with a low concentration of compounds (and possibly sweetened) are sold in the lower segment of the market, characterised by fierce competition. Here, batches must be larger for the sake of efficiency and the concentration of chemical compounds are low for lower costs. Meanwhile, the higher end of the market shows the signs of monopolistic competition with product differentiation, higher quality level, higher prices and smaller batches.

5.1.2 The situation of wine GIs

The place of origin has always been an essential factor of the wine market and labelling geographical names on wines has a long tradition. As the origin is the key of the real, non-reproducible uniqueness of wines, it may be a profitable strategy for wineries of a wine producing country with versatile and good production zones to produce wines that carry characteristics related to their geographical origin.

[12] This dissertation, and in particular this chapter, contains the author's analysis and conclusions based on scientific results, which may confirm, substantiate, but do not bind the author's position on the topic published or transmitted on other platforms for other purposes.

The results suggest that theoretical price-increasing role of GIs manifests in two ways in the Hungarian off-trade wine market. GI use in general (i.e. the use of *any* GI) primarily shows its impacts in the lower price segments, and as the price of wines increases, the differences between the GIs becomes more prominent.

Thus, investing in quality and common branding may have different (decreasing) probabilities of positive returns. Geographical indications with a positive mark-up in higher market segments include, in particular, names of small geographic areas or with rigorous local regulations. In the absence of these, the price premium for even the more famous (e.g. Szekszárd) will run out in the higher segments. All in all, it can be concluded, that an investment to quality, and therefore, stricter rules are needed to increase price premia.

The above seems to be proved interestingly by certain GI regulations, which can hardly be called simple, and are segmented into several quality levels using additional terms to the name itself. On the other hand, the present research confirms that these systems function well and apparently achieve their goal.

The different models showed that in the middle price segment, the price premia of 25-40% of the GIs examined are not significant statistically. This fact raises serious questions about the worth of the use of these names. If they are willingly branded as low-segmented collective brands (such as the PGI Duna-Tisza közi), this is a positive phenomenon as they are fulfilling their role; they distinguish the low-priced products of the community from the more expensive ones. However, this group also contains GIs, where, based on their estimated market position, the returns of the cost of using the name are questionable.

Based on the results of the models described in the dissertation, we can find a total of six designations of origin (all of them are names of wine distrcits and they represent almost the third of the 21 PDOs examined of this kind) with a worse market position than the name of the given wine region (regardless of whether they are PDOs or PGIs). There are three other PDOs where the market position can be considered the same as that of the regional GI. In these cases, there are few arguments in favour of using the name of the wine district instead of the better positioned, possibly better known, or better sounding name of the wine region.

All in all, instead of the PDO/PGI dichotomy, the segmentation of the wine market in Hungary from the point of view of origin shall be based on the added value of GIs.

5.2 Policy implications

This section provides policy implications regarding the wine sector and, in particular geographical indications, drawn from the results of the study.

The results suggest that the lower and the higher end of the wine market shall be treated in a different regulatory manner, and therefore, the control of wine products shall be adjusted to their market situation. Wines sold at larger quantities (and lower prices) shall be controlled on the spot instead of the strict and time-consuming ex-ante control process before their release to the market. On the other hand, wines sold in low quantities and at higher prices (often using GIs or individual terms benefitting of a good reputation) shall be controlled rigorously before entering the market (including strict organoleptic tests).

Geographical indications are of particular importance for the regulation of the wine market, as the Member States have a room of manoeuvre in the single European market practically only in this field, but only indirectly, by shaping the framework. GIs are a quite regulated field of the sector. On the one hand, a large amount these regulations are created by the local communities (mainly specific rules), on the other hand, some vital framework legislation exists, provided by the EU or national governments. This study highlights the vital role of producers' communities in the market success of geographical indications. Thus, policies aimed at empowering and strengthening these communities may result in more valuable GIs as well.

One of the most important lessons of this research on GIs is that wine market policies (such as horizontal rules on GI systems) shall make the differences in quality rules more transparent. A classification of GIs by easy-to-understand quality standards (based on simple indicators of grape and wine quality) may serve as a useful tool. This means that even though GIs shall be treated equally in terms of legal protection, from a marketing or market organisation point of view, different policy approaches shall aim them.

Based on the above, a GI policy works well if it encourages producer communities to decide on the exact market positioning of the GIs they manage and promotes relevant distinction. Given the possibly conflicting interests, especially in the case of existing names, multilevel systems such as Villány and Eger can be a realistically possible compromise solution. Still, the volume placed on the market is so low in the case of so many not positioned GIs that we can talk about bad habits rather than real differences of interest.

Given the vital role of producer communities, difficulties of direct regulatory intervention, and positive research results on regional and national hierarchical systems, the creation of a general framework well-reflecting their market position would serve as the optimal policy option to facilitate the market role and value-adding function of GIs. In other words, as the current designation of origin / geographical indication dichotomy does not really mean a substantial distinction between GIs, I consider it appropriate to create new categories of geographical indications that rely heavily on price and market positioning. Such a system, in addition to leaving the decision-making freedom of the producer communities, facilitates the market prevalence of the geographical indications concerned by providing a framework regulation for each category. This way, geographical indications with higher and lower (possibly negative) implicit prices could be better distinguished. Moreover, the law could set more precise general quality thresholds, and the messages of the various community wine marketing programs would become more credible.

Producers tend to position their single vineyard wines high, which is reflected in the relatively high shadow price of vineyard names on the label. Therefore, it seems to be worth to introduce special regulation on the use of these names as well.

In the light of the above, I propose splitting both PDOs and PGIs into categories of high and low implicit prices. An important principle arising from respect for the free choice of producer communities and avoiding forced decisions is that the new categories shall be the ones that are positioned higher and therefore have stricter rules.

The regulatory framework for the new categories shall pursue to set an appropriate minimum quality level. In order to maintain credibility, comprehensive quality control is needed for these categories, based on rigorous and consistent sensory evaluation (including wine style), which is the most effective way to control the end product. In these categories, for reasons of quality, it is appropriate to establish stricter rules than the existing ones[13] for the quality of the grapes. On the other hand, it is not justified to tighten up the framework for existing categories ("védett eredetű" and "tájbor") and, in some cases, it is possible to relax them (for example, by rethinking controls prior marketing and speeding up the process).

Table 44

Placing existing and potential new GIs in the proposed framework

		EU GI category	
		PDO	**PGI**
market positioning	**high**	names of units smaller than wine districts*, names of certain wine districts*, higher quality tiers of names of wine districts	names of wine regions*
	low or ignored	names of certain wine districts*, lower quality tiers of names of wine districts	names of very large units, other names

*according to the choice of the relevant producer group in the case of existing names

Source: Own composition

As shown in Table 44, the proposed new system is based on the realities of the wine market described by this study, therefore it is based on the existing and functioning solution for PDOs Eger and Villány, which surmounts conflicting interests by introducing several classification levels.

Additional features of the proposed new framework:

- a principle for the orderly presentation of the diverse Hungarian wine origins,
- additional basis for examining applications for protection of new, non-existent geographical indications.

Suggesting new names for the new categories lays out of the scope of the present study, as it may require consideration of some aspects not addressed here. In this respect, it is worth relying on European examples (for example: Austria – DAC / qualitätswein, Italy – DOCG / DOC) or the wine communication pyramid developed by the Hungarian Tourism Agency (MTÜ, 2017).

[13] see Art. 13/A of law No. XVIII of 2004 on grape-growing and wine management

6 SUMMARY

This study aimed to reveal the determinants of wine prices on the Hungarian off-trade market with a particular focus on geographical indications.

The situation of the world market in wine is hard from a producer's point of view. The production still exceeds the consumption, despite the emerging trend of the latter. Moreover, the structure of the consumption has been changing for the last 1-2 decades: occasional consumption is growingly taking the place of daily wine drinking. Given the limited possibilities of adaptation, this renders traditional wine-producing countries in a difficult situation.

Hungary is a middle-sized traditional wine-producing and exporting country showing all the characteristics of this group (e. g. socially embedded sector, low efficiency). The supply is highly fragmented and highly competitive both in grape-growing and winemaking. In such a situation, finding ways of increasing the production value is a crucial factor in the development of the sector.

Wine may be considered an experience good; hence its quality may not be assessed before its consumption. On the market in these goods the consumers often lack adequate information on the quality, and with producers unable to charge a premium for their quality product, goods of poor quality will remain on the market in equilibrium. In such a situation, any form of decreasing or dissolving the information asymmetry between sellers and buyers may contribute to the survival of quality products and their producers.

The review of the literature on wine price determinants showed that five main factors impact wine prices: origin (geographical indications and country of origin), expert ratings, objective quality (chemical composition, the weather of the harvest year, and the age of the wines), traditional labelling elements (grape variety, vintage year and individual brand) and other factors.

In the case of origin, most of the papers reviewed consider geographical indications, and some of them include country of origin. The results suggest that for GIs, most of the impact strongly depends on the actual geographical name rather than merely using any geographical indication, which implies the importance of collective reputation.

Expert ratings seem obvious to impact wine prices. Although the intuition proves to be right, major methodological problems arise with that factor, that is seldom dealt with correctly. Still, all the papers that study the relation of expert ratings (points) and prices revealed positive impact. However, adding character descriptions to the label may associate with lower prices.

Good weather conditions (rainfall before the growing period, low rains before the harvest), higher concentrations of chemical compounds and the age of wines seem to impact wine prices positively.

The three traditional labelling elements seem to have a role in wine prices as well. Wines made of different grape varieties sell at different prices. Harvest years that have a good reputation for the quality may have a severe impact on prices. Winery reputation (or individual brands) may be the reason for price variations between wines with the same GI from the same year and same varietal.

There are some other factors like organic production methods or qualification, macroeconomic cycles, or winery size that may impact wine prices, too.

In order to reveal the factors impacting the wine prices in the Hungarian market, several hedonic price index models were specified. When interpreting the results, one must not forget that hedonic price indices are not intended to estimate consumer behaviour but are supply-oriented, that is, how some supply-side characteristics impact prices. As a control of the results, an LVPLS model was also applied.

The scope of this study is limited to the Hungarian off-trade market of wines, other grapevine products (such as sparkling wine) were excluded. The sample was taken from the off-trade sector. Following the clearing of the sample, 2,672 wines remained, produced by 392 wineries, with 33 of the (then) 37 Hungarian wine GIs were observed. However, 5 GIs were omitted due to the low number of wines in the sample.

In the first step of the study, six hypothesises were developed regarding the price determinants:

1. Certain (but not all) geographical indications have a positive impact on the price.
2. Good individual brands have a positive price premium.
3. The concentration of compounds is positively linked to prices.
4. The age of the wine is positively related to the price.

5. The quantity (lot size) negatively impacts the price.
6. Wines of fashionable varietals or the colour red cost more.

The first five hypothesises were accepted as all results confirmed them, and the sixth hypothesis was partially accepted.

The study confirmed that the use of geographical indications may allow producers to achieve a price premium, hence can be a vehicle of maintaining the presence of traditional quality products in the market despite the potential higher costs. Thus, GIs may be incentives for investment to quality. The high variance of the estimated price premia prove that it is not the use of any GI in general which generates higher prices, but there are rather some geographical indications with higher, some with lower, some without and some even with a negative price premium. This highlights the importance of the factors explaining the market value of GIs detailed in the second step of the research.

The study showed that – considering wine prices – a positive return on investment in quality on the Hungarian wine market is possible at the individual level as well.

Wines of good individual brands cost significantly more on the off-trade market, the price premia that can be achieved is well above the average GI price premium even in the case of Tier2 wineries.

The increase of concentration of the wine (or, in other words, selling less water packaged in a wine bottle) means higher prices. Sugar content has a contradictory impact on the price, depending on the colour; white wines with more (rather residual) sugar content cost more, while rosés and reds with more (rather added) sugar cost less. However, this is in line with the assumptions regarding quality, and the heterogeneity of wines as residual sugar content means riper grapes, and sweetening means uniform flavours. Ageing is also an individual effort to raise quality (in the case of certain types of wine), and the analysis of prices showed that it may pay off as well.

The quantity marketed impacts the price in a negative way, suggesting that not only it is harder to sell wines higher-priced wines in large lots, but vice-versa, expensive wines shall be released to the market in limited volume.

Intuition suggested that a large extent of the differences in wine prices may be attributed to varietal composition. The results showed, that if considered alone, the effect of the grape variety is statistically significant on prices. Nevertheless, the complex models proved the contrary, as in reality, some other factors explain the differences in wine prices that seemed to be caused by varietal composition. Based on the results, the market importance of grape varieties apparently does not include their impact on the price.

The models also suggest that wines with a low concentration of extracts and significant levels of sugar content (i.e. semi-sweet) are sold in the lower segment of the market, characterised by fierce competition. Here, batches must be larger for the sake of efficiency and the concentration of chemical compounds are low for lower costs. Meanwhile, the higher end of the market shows the signs of monopolistic competition with product differentiation, higher quality level, higher prices and smaller batches.

Given their policy relevance, the second step of the study aimed to reveal the factors influencing the market value of geographical indications. Four hypothesises were developed:

1. The market value of a GI linked to a homogenous producer community is high.
2. The stricter the rules of using a GI, the higher its value will be.
3. The higher the barriers to entry are, the higher the market value is.
4. The better the geographic area of a GI is, the higher the market value will be.

Given the limited number of GIs, the methodologic room for manoeuvre of the second step was small. Therefore, the study used simple methods, and restricted regression models were analysed in detail, too.

The estimations of the second step confirmed all hypothesises and showed that local rules on using a GI and the structure of the producers are interdependent.

The analysis underlined the role of collective action as the more homogenous a producer group is, the more likely they behave and think similarly about the geographical indication(s) they use. This draws attention to a new dimension of the positioning of new GIs or repositioning existing ones. To have a meaningful differentiation, a GI shall reflect on special product quality. This can be attained more easily if the quantity of products labelled with the same GI does not vary by group members on a large scale.

The role of delimited production area is an essential issue in case of GIs regarding the link between origin and the quality of the final product. The actual size and quality of the production area is an important policy tool as it serves as a barrier to entry into the market. Thus, all initiatives on the enlargement of the production area shall be treated with particular caution.

The valuable information on GI products is not that they are generally special in some mystical way – it is *why* they are special. A well-functioning GI shall bear this information and market organisation policies shall reflect that.

The results suggest that the Hungarian off-trade wine market can be split into two parts. Wines with a low concentration of compounds (and possibly sweetened) are sold in the lower segment of the market, characterised by fierce competition. Here, batches must be larger for the sake of efficiency and the concentration of chemical compounds are low for lower costs. Meanwhile, the higher end of the market shows the signs of monopolistic competition with product differentiation, higher quality level, higher prices and smaller batches.

The theoretical price-increasing role of GIs manifests in two ways in the Hungarian off-trade wine market. GI use in general primarily shows its positive impacts in the lower price segments, and as the price of wines increases, the differences between the GIs becomes more prominent. In addition, segmentation of GIs into several quality levels using additional terms to the name itself seem to pay off as the upper tiers of these systems show high implicit prices

The models showed that in the middle price segment, the price premia of 25-40% of the GIs examined are not significant statistically. In a notable number (3+6 out of 21 wine district names) of cases, the estimated price premium of the name of a larger unit (the regional GI) equals or even exceeds that of smaller districts.

Consequently, instead of the PDO/PGI dichotomy, the segmentation of the wine market in Hungary from the point of view of origin shall be based on the added value of GIs.

Finally, a new regulatory framework for Hungarian wine GIs is proposed based on these findings establishing two new categories for PDOs and PGIs with elevated quality level and stricter controls.

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LIST OF THE AUTHOR'S PUBLICATIONS OF THE TOPIC

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Gál, P. (2020): The Determinants of Wine Prices: A Systematic Literature Review Competitio 19(1) DOI: 10.21845/comp/2020/1-2/1

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APPENDICES

Appendix I. Presentation of the sample

Table I.1

Descriptive statistics for the dummy variables of the 1st step

Variable	Mean	Std.Dev.	Min	Max	Frequency
Badacsony	0.0314	0.1745	0	1	84
Balaton	0.0299	0.1705	0	1	80
Balatonboglár	0.0580	0.2338	0	1	155
Balaton-felvidék	0.0094	0.0963	0	1	25
Balatonfüred-Csopak	0.0408	0.1978	0	1	109
Bükk	0.0022	0.0473	0	1	6
Duna	0.0022	0.0473	0	1	6
Dunántúli	0.0311	0.1735	0	1	83
Duna-Tisza közi	0.0348	0.1833	0	1	93
Eger	0.0689	0.2533	0	1	184
Eger Classicus	0.0505	0.2191	0	1	135
Eger Superior	0.0090	0.0944	0	1	24
Eger Grand Superior	0.0026	0.0511	0	1	7
Eger before 2010	0.0067	0.0818	0	1	18
Etyek-Buda	0.0247	0.1552	0	1	66
Felső-Magyarország	0.0427	0.2021	0	1	114
Hajós-Baja	0.0150	0.1215	0	1	40
Káli	0.0022	0.0473	0	1	6
Kunság	0.0352	0.1843	0	1	94
Mátra	0.0475	0.2128	0	1	127
Mór	0.0052	0.0722	0	1	14
Nagy-Somló	0.0157	0.1244	0	1	42
Neszmély	0.0124	0.1105	0	1	33
Pannon	0.0064	0.0795	0	1	17
Pannonhalma	0.0086	0.0924	0	1	23
Pécs	0.0168	0.1287	0	1	45
Sopron/Ödenburg	0.0251	0.1564	0	1	67
Szekszárd	0.1171	0.3216	0	1	313
Tokaj	0.1291	0.3354	0	1	345
Tokaj wine speciality	0.0348	0.1833	0	1	93
Tokaj non-wine speciality	0.0943	0.2923	0	1	252
Tolna	0.0120	0.1088	0	1	32
Villány	0.1407	0.3478	0	1	376
Villány Classicus	0.1040	0.3054	0	1	278
Villány Pérmium	0.0367	0.1880	0	1	98
Zala	0.0026	0.0511	0	1	7
Single vineyard wine	0.0389	0.1934	0	1	104
Tier1 individual brand	0.1677	0.3736	0	1	448
Tier1 individual brand	0.1853	0.3886	0	1	495
Red-Bordeaux variety	0.1838	0.3874	0	1	491
Red-other variety	0.1853	0.3886	0	1	495
Red-variety not indicated	0.0258	0.1586	0	1	69
White-other variety	0.3664	0.4819	0	1	979
White-variety not indicated	0.0202	0.1407	0	1	54
Other Muscat variety	0.0528	0.2236	0	1	141
Cserszegi or Irsai	0.0427	0.2021	0	1	114
White	0.4820	0.4998	0	1	1288
Non-white	0.5180	0.4998	0	1	1384

N=2672

Source: own composition.

Table I.2

Descriptive statistics for the LVPLS model of the 1st step

	Price	Quantity	Actual alcohol	Sugar	Sugar-free extract	pH
Min	194.85	250	7.14	0	15.6	2.88
Max	23980	507284	16.45	162.7	46.8	4.01
Mean	2071.949	20285.47	12.61217	5.310013	24.70351	3.491669
Standard deviation	1937.917	35811.24	1.159611	13.09406	4.475082	0.166944
Median	1525	7540	12.59	1.3	24.3	3.49
Unit of measurement	HUF/ 0.75 litre	litre	%vol	g/litre	g/litre	-

Source: own composition.

Appendix II. Results of the 1st step

1. Restricted Models A2.R1-A6.R1

```
. *0,1 EGYBEN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm
hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj
tolna villany zala, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  1128.2197

Iteration  1: sum of abs. weighted deviations =  1175.8411
Iteration  2: sum of abs. weighted deviations =  1064.2082
Iteration  3: sum of abs. weighted deviations =   922.0945
Iteration  4: sum of abs. weighted deviations =  858.41109
Iteration  5: sum of abs. weighted deviations =  810.01297
Iteration  6: sum of abs. weighted deviations =  787.56083
Iteration  7: sum of abs. weighted deviations =  761.65314
Iteration  8: sum of abs. weighted deviations =  746.21476
Iteration  9: sum of abs. weighted deviations =  731.86815
Iteration 10: sum of abs. weighted deviations =  698.20091
Iteration 11: sum of abs. weighted deviations =  685.03124
Iteration 12: sum of abs. weighted deviations =  657.24933
Iteration 13: sum of abs. weighted deviations =  638.10321
Iteration 14: sum of abs. weighted deviations =  625.85788
Iteration 15: sum of abs. weighted deviations =  592.92736
Iteration 16: sum of abs. weighted deviations =   576.2167
Iteration 17: sum of abs. weighted deviations =  568.05833
Iteration 18: sum of abs. weighted deviations =  560.14338
note:  alternate solutions exist
Iteration 19: sum of abs. weighted deviations =  556.07883
Iteration 20: sum of abs. weighted deviations =  552.92569
Iteration 21: sum of abs. weighted deviations =  547.53155
Iteration 22: sum of abs. weighted deviations =  540.79298
Iteration 23: sum of abs. weighted deviations =  538.37543
Iteration 24: sum of abs. weighted deviations =  537.45346
Iteration 25: sum of abs. weighted deviations =  535.05644
Iteration 26: sum of abs. weighted deviations =  533.48292
Iteration 27: sum of abs. weighted deviations =   533.2186
Iteration 28: sum of abs. weighted deviations =  532.52081
Iteration 29: sum of abs. weighted deviations =  532.04772
Iteration 30: sum of abs. weighted deviations =  531.39797

.1 Quantile regression                              Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations  531.398                    Pseudo R2     =    0.2735
```

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
badacsony	1.388799	.021581	64.35	0.000	1.346482	1.431116
balaton	.7749891	.0214006	36.21	0.000	.7330255	.8169528
bb	1.043615	.0178315	58.53	0.000	1.00865	1.07858
bfelv	1.202299	.0252023	47.71	0.000	1.152881	1.251717
bfcs	1.207061	.0198266	60.88	0.000	1.168184	1.245939
bukk	.9829173	.0238189	41.27	0.000	.9362118	1.029623
duna	1.207312	.0221326	54.55	0.000	1.163913	1.250711
dunantuli	.6003423	.0209537	28.65	0.000	.5592549	.6414296
dtk	-.2860112	.0190552	-15.01	0.000	-.3233759	-.2486466
eger	.8492069	.0173263	49.01	0.000	.8152324	.8831815
etyekbuda	1.043615	.0229982	45.38	0.000	.9985191	1.088712
fm	.5705447	.0198255	28.78	0.000	.5316697	.6094197
hb	1.100839	.0283867	38.78	0.000	1.045177	1.156502
kali	1.645566	.0238189	69.09	0.000	1.598861	1.692272
kunsag	.9829173	.0208943	47.04	0.000	.9419465	1.023888
matra	.696486	.0191763	36.32	0.000	.6588839	.7340881
mor	1.381265	.0187268	73.76	0.000	1.344544	1.417985
nsomlo	1.100839	.0222395	49.50	0.000	1.05723	1.144448
neszmely	1.288891	.0296082	43.53	0.000	1.230834	1.346949
pannon	1.187109	.0332645	35.69	0.000	1.121882	1.252336
phalma	1.469676	.0336802	43.64	0.000	1.403634	1.535718
pecs	1.207312	.0261023	46.25	0.000	1.156129	1.258495
sopron	1.543784	.0227859	67.75	0.000	1.499104	1.588464
szekszard	1.206311	.0158835	75.95	0.000	1.175166	1.237457
tokaj	1.301712	.0156222	83.32	0.000	1.271079	1.332345

```
       tolna |   .6319475   .0303009    20.86   0.000     .5725316    .6913635
     villany |   1.206311   .0155177    77.74   0.000     1.175883    1.236739
        zala |   1.206311   .0228359    52.83   0.000     1.161533    1.251089
       _cons |   5.700444    .013413   425.00   0.000     5.674143    5.726745
------------------------------------------------------------------------------

. estimates store qe_korl10

.
. *0,25 EGYBEN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm
hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj
tolna villany zala, quantile(25)
Iteration  1:  WLS sum of weighted deviations =   1259.224

Iteration  1: sum of abs. weighted deviations =  1270.9792
note:  alternate solutions exist
Iteration  2: sum of abs. weighted deviations =  1215.8206
Iteration  3: sum of abs. weighted deviations =  1155.0979
Iteration  4: sum of abs. weighted deviations =  1129.9687
note:  alternate solutions exist
Iteration  5: sum of abs. weighted deviations =  1113.9396
Iteration  6: sum of abs. weighted deviations =  1105.1258
Iteration  7: sum of abs. weighted deviations =  1096.5327
Iteration  8: sum of abs. weighted deviations =  1090.9494
Iteration  9: sum of abs. weighted deviations =  1076.1692
Iteration 10: sum of abs. weighted deviations =   1068.439
Iteration 11: sum of abs. weighted deviations =   1063.072
Iteration 12: sum of abs. weighted deviations =  1052.7193
Iteration 13: sum of abs. weighted deviations =  1042.2957
note:  alternate solutions exist
Iteration 14: sum of abs. weighted deviations =  1037.4449
Iteration 15: sum of abs. weighted deviations =  1019.4836
note:  alternate solutions exist
Iteration 16: sum of abs. weighted deviations =  1015.0004
Iteration 17: sum of abs. weighted deviations =    1012.55
Iteration 18: sum of abs. weighted deviations =  1010.2085
Iteration 19: sum of abs. weighted deviations =  1009.1281
Iteration 20: sum of abs. weighted deviations =  1007.8979
Iteration 21: sum of abs. weighted deviations =  1006.6078
Iteration 22: sum of abs. weighted deviations =   1005.211
Iteration 23: sum of abs. weighted deviations =  1003.7572
Iteration 24: sum of abs. weighted deviations =  1003.1967
Iteration 25: sum of abs. weighted deviations =  1002.4852
Iteration 26: sum of abs. weighted deviations =  1001.8333
Iteration 27: sum of abs. weighted deviations =  1001.7841
Iteration 28: sum of abs. weighted deviations =  1001.6802

.25 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations  1001.68                    Pseudo R2     =    0.2039

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   1.457481   .0170751    85.36   0.000        1.424    1.490963
     balaton |    .828289   .0171017    48.43   0.000     .7947549    .8618231
          bb |   1.147084   .0147544    77.75   0.000     1.118153    1.176015
       bfelv |   1.458148   .0252799    57.68   0.000     1.408578    1.507719
        bfcs |   1.451459   .0159789    90.84   0.000     1.420127    1.482792
        bukk |    1.64047   .0398882    41.13   0.000     1.562255    1.718685
        duna |   1.052683   .0249244    42.23   0.000      1.00381    1.101557
   dunantuli |   .5401897   .0160803    33.59   0.000     .5086584    .5717211
         dtk |  -.1546283   .0164018    -9.43   0.000    -.1867899   -.1224666
        eger |   1.226636   .0143992    85.19   0.000     1.198402    1.254871
   etyekbuda |   1.234171   .0180185    68.49   0.000     1.198839    1.269503
          fm |   .9462109   .0157523    60.07   0.000     .9153227     .977099
          hb |   1.052683   .0208891    50.39   0.000     1.011723    1.093644
        kali |   2.082303   .0413799    50.32   0.000     2.001162    2.163443
      kunsag |   1.052683   .0164516    63.99   0.000     1.020424    1.084943
       matra |   .7636671   .0153849    49.64   0.000     .7334993    .7938349
         mor |   1.234171   .0271571    45.45   0.000      1.18092    1.287422
      nsomlo |   1.457481   .0196517    74.17   0.000     1.418947    1.496016
    neszmely |   1.234171   .0228263    54.07   0.000     1.189412     1.27893
      pannon |   1.147084   .0288265    39.79   0.000     1.090559    1.203609
      phalma |   1.583312   .0252896    62.61   0.000     1.533722    1.632901
        pecs |   1.147994   .0190422    60.29   0.000     1.110654    1.185333
```

```
      sopron |   1.458148    .017282    84.37   0.000     1.424261    1.492036
   szekszard |    1.43112   .0133034   107.58   0.000     1.405034    1.457206
       tokaj |   1.612299   .0131841   122.29   0.000     1.586447    1.638151
       tolna |   1.042633   .0231719    45.00   0.000     .9971962     1.08807
     villany |   1.388441   .0130344   106.52   0.000     1.362882       1.414
        zala |   1.314278    .037192    35.34   0.000      1.24135    1.387206
       _cons |   5.855072   .0116752   501.50   0.000     5.832179    5.877965
------------------------------------------------------------------------------

. estimates store qe_korl25

.
. *0,5 EGYBEN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm
hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj
tolna villany zala
Iteration  1:  WLS sum of weighted deviations =  1357.6986

Iteration  1: sum of abs. weighted deviations =  1356.4148
Iteration  2: sum of abs. weighted deviations =  1354.1655
Iteration  3: sum of abs. weighted deviations =  1353.1123
Iteration  4: sum of abs. weighted deviations =  1351.7516
Iteration  5: sum of abs. weighted deviations =   1351.002
Iteration  6: sum of abs. weighted deviations =  1350.2791
Iteration  7: sum of abs. weighted deviations =  1349.3968
Iteration  8: sum of abs. weighted deviations =  1348.7699
Iteration  9: sum of abs. weighted deviations =  1348.4018
Iteration 10: sum of abs. weighted deviations =  1348.3211
Iteration 11: sum of abs. weighted deviations =  1348.2076
Iteration 12: sum of abs. weighted deviations =  1347.4446
Iteration 13: sum of abs. weighted deviations =  1347.4387
Iteration 14: sum of abs. weighted deviations =  1347.4387
Iteration 15: sum of abs. weighted deviations =  1347.2296
Iteration 16: sum of abs. weighted deviations =  1347.1551
Iteration 17: sum of abs. weighted deviations =  1347.0621
Iteration 18: sum of abs. weighted deviations =  1347.0621
Iteration 19: sum of abs. weighted deviations =    1347.05
Iteration 20: sum of abs. weighted deviations =  1346.9367
Iteration 21: sum of abs. weighted deviations =  1346.9367
Iteration 22: sum of abs. weighted deviations =  1346.9119

Median regression                                    Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 1346.912                     Pseudo R2     =    0.1433

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .8484097   .0313955    27.02   0.000     .7868474    .9099719
     balaton |   .3680673   .0316807    11.62   0.000     .3059457    .4301888
          bb |   .5112705   .0274178    18.65   0.000      .457508    .5650331
       bfelv |   .6371007   .0459855    13.85   0.000     .5469295    .7272719
        bfcs |   .6937032   .0294758    23.53   0.000     .6359052    .7515011
        bukk |   .6942592   .0720866     9.63   0.000     .5529073     .835611
        duna |   .4065771   .0798362     5.09   0.000     .2500294    .5631248
   dunantuli |   2.20e-13    .031392     0.00   1.000    -.0615554    .0615554
         dtk |  -.8904862   .0301422   -29.54   0.000    -.9495909   -.8313816
        eger |   .6365123   .0266683    23.87   0.000     .5842194    .6888052
   etyekbuda |   .4422302   .0328732    13.45   0.000     .3777705      .50669
          fm |   .4641466   .0292513    15.87   0.000     .4067888    .5215044
          hb |   .3207769   .0389901     8.23   0.000     .2443228    .3972311
        kali |   1.198396   .0798362    15.01   0.000     1.041848    1.354943
      kunsag |   .3296161   .0303911    10.85   0.000     .2700234    .3892087
       matra |   .2804255   .0283739     9.88   0.000     .2247883    .3360628
         mor |   .5112705   .0555164     9.21   0.000     .4024106    .6201304
      nsomlo |   .8949299   .0383697    23.32   0.000     .8196922    .9701675
    neszmely |   .4422302    .040197    11.00   0.000     .3634094     .521051
      pannon |   .4065771    .053232     7.64   0.000     .3021965    .5109577
      phalma |   .7991195   .0474319    16.85   0.000     .7061121    .8921268
        pecs |   .5119376   .0363913    14.07   0.000     .4405792     .583296
      sopron |   .7639923   .0333207    22.93   0.000      .698655    .8293296
   szekszard |   .7430491   .0249331    29.80   0.000     .6941589    .7919394
       tokaj |   1.201746   .0246686    48.72   0.000     1.153374    1.250118
       tolna |   .4780359   .0410785    11.64   0.000     .3974866    .5585853
     villany |   .7737889   .0244854    31.60   0.000     .7257765    .8218014
        zala |    .575851   .0693688     8.30   0.000     .4398282    .7118737
       _cons |   6.801283   .0220706   308.16   0.000     6.758006     6.84456
```

```
------------------------------------------------------------------------------

. estimates store qe_korl50

.
. *0,75 EGYBEN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm
hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj
tolna villany zala, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1304.6413

Iteration  1: sum of abs. weighted deviations =  1319.4331
note:  alternate solutions exist
Iteration  2: sum of abs. weighted deviations =  1291.3358
Iteration  3: sum of abs. weighted deviations =  1262.9972
Iteration  4: sum of abs. weighted deviations =  1248.1549
note:  alternate solutions exist
Iteration  5: sum of abs. weighted deviations =  1231.0654
Iteration  6: sum of abs. weighted deviations =  1215.7422
Iteration  7: sum of abs. weighted deviations =  1207.0304
Iteration  8: sum of abs. weighted deviations =  1203.6992
Iteration  9: sum of abs. weighted deviations =  1199.0703
Iteration 10: sum of abs. weighted deviations =  1185.0084
Iteration 11: sum of abs. weighted deviations =  1182.1879
note:  alternate solutions exist
Iteration 12: sum of abs. weighted deviations =  1178.9921
note:  alternate solutions exist
Iteration 13: sum of abs. weighted deviations =  1174.5718
Iteration 14: sum of abs. weighted deviations =  1167.9943
Iteration 15: sum of abs. weighted deviations =  1163.8797
Iteration 16: sum of abs. weighted deviations =  1157.1866
Iteration 17: sum of abs. weighted deviations =  1156.0543
Iteration 18: sum of abs. weighted deviations =  1153.0623
note:  alternate solutions exist
Iteration 19: sum of abs. weighted deviations =  1152.3763
note:  alternate solutions exist
Iteration 20: sum of abs. weighted deviations =  1151.2547
Iteration 21: sum of abs. weighted deviations =  1150.0101
Iteration 22: sum of abs. weighted deviations =   1149.111
Iteration 23: sum of abs. weighted deviations =  1147.7854
Iteration 24: sum of abs. weighted deviations =  1146.9639
Iteration 25: sum of abs. weighted deviations =  1146.9605
Iteration 26: sum of abs. weighted deviations =  1146.7792
Iteration 27: sum of abs. weighted deviations =  1146.3678
Iteration 28: sum of abs. weighted deviations =  1145.9559
Iteration 29: sum of abs. weighted deviations =   1145.514
Iteration 30: sum of abs. weighted deviations =  1145.4411

.75 Quantile regression                            Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 1145.441                   Pseudo R2     =    0.1645

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .4567585   .1015933     4.50   0.000     .2575481    .6559689
     balaton |  -.0380845   .1018586    -0.37   0.709    -.2378152    .1616462
          bb |   .1466036    .088453     1.66   0.098    -.0268405    .3200477
       bfelv |  -.0159154   .1396269    -0.11   0.909    -.2897045    .2578737
        bfcs |    .274437   .0953584     2.88   0.004     .0874522    .4614217
        bukk |   .0462809   .2418091     0.19   0.848    -.4278733     .520435
        duna |   .1000834   .2418091     0.41   0.679    -.3740708    .5742375
   dunantuli |  -.2370558    .100951    -2.35   0.019    -.4350067   -.0391048
         dtk |  -1.154347   .0981108   -11.77   0.000    -1.346729   -.9619656
        eger |   .4564247    .086411     5.28   0.000     .2869846    .6258648
   etyekbuda |  -.0005264   .1077639    -0.00   0.996    -.2118366    .2107838
          fm |   .1668515    .094314     1.77   0.077    -.0180851    .3517882
          hb |  -.2373891   .1267299    -1.87   0.061    -.4858889    .0111108
        kali |   .8620014   .2418091     3.56   0.000     .3878472    1.336156
      kunsag |  -.2370558   .0959742    -2.47   0.014     -.425248   -.0488636
       matra |  -.1724753    .091639    -1.88   0.060    -.3521667     .007216
         mor |  -.2363887    .177404    -1.33   0.183    -.5842534     .111476
      nsomlo |   .5936174   .1198621     4.95   0.000     .3585844    .8286505
    neszmely |  -.0272088   .1299083    -0.21   0.834     -.281941    .2275234
      pannon |  -.2430778   .1721221    -1.41   0.158    -.5805855      .09443
      phalma |    .274437   .1307004     2.10   0.036     .0181515    .5307224
        pecs |  -.0005264   .1212485    -0.00   0.997     -.238278    .2372252
```

```
      sopron |   .6109095   .1068593     5.72   0.000     .4013732    .8204457
   szekszard |   .3550949   .0803504     4.42   0.000     .1975388     .512651
       tokaj |   1.149655   .0794968    14.46   0.000     .9937731    1.305538
       tolna |  -.1532741   .1370466    -1.12   0.263    -.4220036    .1154555
     villany |   .5306282   .0789857     6.72   0.000     .3757481    .6855083
        zala |   .0671668   .2175309     0.31   0.758    -.3593812    .4937148
       _cons |   7.549609   .0711313   106.14   0.000     7.410131    7.689088
------------------------------------------------------------------------------

. estimates store qe_korl75

.
. *0,9 EGYBEN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm
hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj
tolna villany zala, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1199.5366

Iteration  1: sum of abs. weighted deviations =  1234.4935
Iteration  2: sum of abs. weighted deviations =  1136.8379
Iteration  3: sum of abs. weighted deviations =  1029.2341
Iteration  4: sum of abs. weighted deviations =  970.74211
Iteration  5: sum of abs. weighted deviations =  921.77668
Iteration  6: sum of abs. weighted deviations =  885.64772
Iteration  7: sum of abs. weighted deviations =  868.59461
Iteration  8: sum of abs. weighted deviations =    848.468
Iteration  9: sum of abs. weighted deviations =   839.1522
Iteration 10: sum of abs. weighted deviations =  809.42256
Iteration 11: sum of abs. weighted deviations =  789.05525
Iteration 12: sum of abs. weighted deviations =  777.61218
Iteration 13: sum of abs. weighted deviations =  762.62824
Iteration 14: sum of abs. weighted deviations =  748.23411
Iteration 15: sum of abs. weighted deviations =  730.82531
Iteration 16: sum of abs. weighted deviations =  717.16233
Iteration 17: sum of abs. weighted deviations =   704.1349
Iteration 18: sum of abs. weighted deviations =  693.60704
note:  alternate solutions exist
Iteration 19: sum of abs. weighted deviations =  689.78231
Iteration 20: sum of abs. weighted deviations =  686.58673
Iteration 21: sum of abs. weighted deviations =  683.47211
Iteration 22: sum of abs. weighted deviations =  681.66185
Iteration 23: sum of abs. weighted deviations =  680.55559
Iteration 24: sum of abs. weighted deviations =  676.76875
Iteration 25: sum of abs. weighted deviations =  675.92029
Iteration 26: sum of abs. weighted deviations =   674.9997
Iteration 27: sum of abs. weighted deviations =  673.99017
Iteration 28: sum of abs. weighted deviations =  672.38636
Iteration 29: sum of abs. weighted deviations =  670.81226
Iteration 30: sum of abs. weighted deviations =  670.09261

.9 Quantile regression                              Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 670.0926                    Pseudo R2     =    0.2011

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .2836084   .1753878     1.62   0.106    -.0603028    .6275197
     balaton |  -.2137032   .1796563    -1.19   0.234    -.5659844    .1385781
          bb |  -.0163937    .152173    -0.11   0.914    -.3147839    .2819965
       bfelv |   -.517169   .2453747    -2.11   0.035    -.9983149   -.0360231
        bfcs |  -.0057077   .1636014    -0.03   0.972    -.3265075     .315092
        bukk |   .0267391   .1906545     0.14   0.888     -.347108    .4005863
        duna |  -.1424761   .1906545    -0.75   0.455    -.5163232    .2313711
   dunantuli |   -.451211   .1764078    -2.56   0.011    -.7971223   -.1052996
         dtk |  -1.497998   .1715929    -8.73   0.000    -1.834468   -1.161528
        eger |   .3492622   .1496491     2.33   0.020     .0558209    .6427035
   etyekbuda |  -.0557251   .1850292    -0.30   0.763    -.4185419    .3070917
          fm |  -.1553707   .1635937    -0.95   0.342    -.4761554     .165414
          hb |  -.6129794   .2224073    -2.76   0.006    -1.049089   -.1768694
        kali |   .7612362   .1906545     3.99   0.000      .387389    1.135083
      kunsag |   -.664299   .1707532    -3.89   0.000    -.9991224   -.3294756
       matra |  -.5176239   .1592809    -3.25   0.001    -.8299517   -.2052961
         mor |  -.6124792   .2950535    -2.08   0.038    -1.191038     -.03392
      nsomlo |   .0293741   .2152939     0.14   0.891    -.3927875    .4515357
    neszmely |  -.5926766   .2037812    -2.91   0.004    -.9922634   -.1930899
      pannon |  -.7755866   .2558795    -3.03   0.002    -1.277331   -.2738423
```

```
      phalma |  -.2137032   .2604336    -0.82   0.412    -.7243776    .2969713
        pecs |  -.3127451   .2064432    -1.51   0.130    -.7175518    .0920616
      sopron |   .3137617    .183579     1.71   0.088    -.0462114    .6737348
   szekszard |   .0804176   .1393225     0.58   0.564    -.1927745    .3536098
       tokaj |   1.295952   .1378021     9.40   0.000     1.025741    1.566163
       tolna |  -.2513146   .2358899    -1.07   0.287    -.7138622    .2112329
     villany |   .4348392   .1365983     3.18   0.001     .1669888    .7026897
        zala |  -.4385262   .1839207    -2.38   0.017    -.7991692   -.0778831
       _cons |   8.213382    .122637    66.97   0.000     7.972908    8.453856
------------------------------------------------------------------------------

. estimates store qe_korl90
```

2. Restricted Models X2-6

```
. reg logp tier1 tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F(  2,  2669) =  163.77
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1045
                                                       Root MSE      =  .76098

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tier1 |   .5039443   .0408424    12.34   0.000     .4238583    .5840304
       tier2 |   .5759177   .0365659    15.75   0.000     .5042174    .6476179
       _cons |   7.282442   .0186515   390.45   0.000     7.245869    7.319015
------------------------------------------------------------------------------

. estimates store R12

.
. reg logp cme2 fcukor nfcukor, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F(  3,  2668) =   94.63
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3054
                                                       Root MSE      =  .67029

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0006059   .0001461     4.15   0.000     .0003194    .0008923
      fcukor |   .0017702   .0010931     1.62   0.105    -.0003732    .0039136
     nfcukor |  -.0274584   .0021731   -12.64   0.000    -.0317196   -.0231972
       _cons |   7.087984   .0901572    78.62   0.000     6.911199    7.264769
------------------------------------------------------------------------------

. estimates store R13

.
. reg logp kor, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F(  1,  2670) =  922.18
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3689
                                                       Root MSE      =   .6387

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         kor |   .2542893   .0083737    30.37   0.000     .2378696    .2707089
       _cons |   6.828006   .0221707   307.97   0.000     6.784533     6.87148
------------------------------------------------------------------------------

. estimates store R14
```

```
.
. reg logp logq, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F(  1,  2670) =  960.46
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3073
                                                       Root MSE      =  .66914

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.3220862   .0103928   -30.99   0.000     -.342465   -.3017075
       _cons |   10.35461   .0945296   109.54   0.000     10.16925    10.53997
------------------------------------------------------------------------------

. estimates store R15

.
. reg logp vbordo vegyeb vnem ffajta fnem muskegyeb csfi, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F(  7,  2664) =   67.36
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0939
                                                       Root MSE      =  .76618

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      vbordo |   .6469783   .0422939    15.30   0.000     .5640462    .7299104
      vegyeb |   .3684426   .0422594     8.72   0.000     .2855781    .4513071
        vnem |   -.070221   .1341321    -0.52   0.601    -.3332345    .1927925
      ffajta |   .5340655   .0357385    14.94   0.000     .4639875    .6041434
        fnem |   .0369687   .1562498     0.24   0.813    -.2694145    .3433519
   muskegyeb |   .1825606   .0701433     2.60   0.009     .0450197    .3201014
        csfi |  -.1366579   .0458099    -2.98   0.003    -.2264844   -.0468313
       _cons |    7.08807      .0242   292.90   0.000     7.040617    7.135523
------------------------------------------------------------------------------

.
end of do-file
. qreg logp tier1 tier2, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  1306.3184

Iteration  1: sum of abs. weighted deviations =  1316.7836
Iteration  2: sum of abs. weighted deviations =  890.37428
Iteration  3: sum of abs. weighted deviations =  775.40054
Iteration  4: sum of abs. weighted deviations =   651.2924

.1 Quantile regression                               Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations 651.2924                     Pseudo R2     =    0.1096

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tier1 |   .7174401   .0676179    10.61   0.000     .5848514    .8500289
       tier2 |   .8620214    .065172    13.23   0.000     .7342288    .9898141
       _cons |   6.308098   .0300957   209.60   0.000     6.249085    6.367112
------------------------------------------------------------------------------

. estimates store R22

.
. qreg logp cme2 fcukor nfcukor, quantile(10)
Iteration  1:  WLS sum of weighted deviations =   1203.316

Iteration  1: sum of abs. weighted deviations =  1115.1904
Iteration  2: sum of abs. weighted deviations =    1070.07
Iteration  3: sum of abs. weighted deviations =   1068.991
Iteration  4: sum of abs. weighted deviations =   1066.968
Iteration  5: sum of abs. weighted deviations =  952.62353
Iteration  6: sum of abs. weighted deviations =  669.98958
Iteration  7: sum of abs. weighted deviations =  665.74328
```

```
Iteration  8: sum of abs. weighted deviations =  665.30363
Iteration  9: sum of abs. weighted deviations =  658.51467
Iteration 10: sum of abs. weighted deviations =  654.88434
Iteration 11: sum of abs. weighted deviations =  654.82787
Iteration 12: sum of abs. weighted deviations =  651.61476
Iteration 13: sum of abs. weighted deviations =  651.48306
Iteration 14: sum of abs. weighted deviations =  651.48081
Iteration 15: sum of abs. weighted deviations =  651.48047

.1 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations 651.4805                   Pseudo R2     =    0.1094

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0006093   .0001233     4.94   0.000     .0003675     .000851
      fcukor |  -.0014002   .0010115    -1.38   0.166    -.0033836    .0005832
     nfcukor |   -.043822    .002561   -17.11   0.000    -.0488438   -.0388002
       _cons |   6.346071   .0807713    78.57   0.000      6.18769    6.504452
------------------------------------------------------------------------------

. estimates store R23

.
. qreg logp kor, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  1196.5011

Iteration  1: sum of abs. weighted deviations =  1194.2811
Iteration  2: sum of abs. weighted deviations =  1026.3112
Iteration  3: sum of abs. weighted deviations =  654.78724
Iteration  4: sum of abs. weighted deviations =  639.57349
Iteration  5: sum of abs. weighted deviations =  638.25847
Iteration  6: sum of abs. weighted deviations =  636.62064
Iteration  7: sum of abs. weighted deviations =  636.61797

.1 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations  636.618                   Pseudo R2     =    0.1297

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         kor |   .2274562   .0173421    13.12   0.000     .1934509    .2614615
       _cons |   6.082462   .0521982   116.53   0.000     5.980109    6.184815
------------------------------------------------------------------------------

. estimates store R24

.
. qreg logp logq, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  1165.5181

Iteration  1: sum of abs. weighted deviations =  1171.3215
Iteration  2: sum of abs. weighted deviations =  786.94022
Iteration  3: sum of abs. weighted deviations =  536.85041
Iteration  4: sum of abs. weighted deviations =  533.94743
Iteration  5: sum of abs. weighted deviations =  533.29138
Iteration  6: sum of abs. weighted deviations =    533.228
Iteration  7: sum of abs. weighted deviations =  533.22562

.1 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations 533.2256                   Pseudo R2     =    0.2710

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.3356493    .015423   -21.76   0.000    -.3658916    -.305407
       _cons |   9.738935   .1391676    69.98   0.000     9.466048    10.01182
------------------------------------------------------------------------------

. estimates store R25

.
. qreg logp vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(10)
Iteration  1:  WLS sum of weighted deviations =   1306.108
```

```
Iteration  1: sum of abs. weighted deviations =   1313.626
Iteration  2: sum of abs. weighted deviations =  1071.7059
Iteration  3: sum of abs. weighted deviations =  927.15462
Iteration  4: sum of abs. weighted deviations =  813.56814
Iteration  5: sum of abs. weighted deviations =  771.48114
Iteration  6: sum of abs. weighted deviations =  744.39506
Iteration  7: sum of abs. weighted deviations =   733.0422
Iteration  8: sum of abs. weighted deviations =  702.43302
Iteration  9: sum of abs. weighted deviations =   676.9297

.1 Quantile regression                              Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations 676.9297                    Pseudo R2     =    0.0746

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      vbordo |   .2910395   .1076533     2.70   0.007     .0799469     .502132
      vegyeb |  -.1958656   .1061226    -1.85   0.065    -.4039567    .0122254
        vnem |  -1.091352   .1378384    -7.92   0.000    -1.361633   -.8210705
      ffajta |   .1912503   .0959308     1.99   0.046      .003144    .3793566
        fnem |  -.8745723   .1993722    -4.39   0.000    -1.265512   -.4836322
   muskegyeb |  -.1105223   .1523384    -0.73   0.468    -.4092358    .1881913
        csfi |   -.109271   .1629267    -0.67   0.502    -.4287467    .2102046
       _cons |   6.505784   .0829183    78.46   0.000     6.343193    6.668375
------------------------------------------------------------------------------

.
end of do-file

. do "C:\Users\peter\AppData\Local\Temp\STD00000000.tmp"

.
. *3 - qreg 0.25
.
. qreg logp tier1 tier2, quantile(25)
Iteration  1:  WLS sum of weighted deviations =  1423.5345

Iteration  1: sum of abs. weighted deviations =  1429.8747
Iteration  2: sum of abs. weighted deviations =   1292.177
Iteration  3: sum of abs. weighted deviations =  1231.5715
note:  alternate solutions exist
Iteration  4: sum of abs. weighted deviations =  1167.3179

.25 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 1167.318                    Pseudo R2     =    0.0722

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tier1 |   .4192586   .0462408     9.07   0.000     .3285872      .50993
       tier2 |   .5108256   .0441017    11.58   0.000     .4243487    .5973026
       _cons |   6.866933   .0211475   324.72   0.000     6.825466      6.9084
------------------------------------------------------------------------------

. estimates store R32

.
. qreg logp cme2 fcukor nfcukor, quantile(25)
Iteration  1:  WLS sum of weighted deviations =  1281.7401

Iteration  1: sum of abs. weighted deviations =  1283.4839
Iteration  2: sum of abs. weighted deviations =   1266.733
Iteration  3: sum of abs. weighted deviations =  1265.2859
Iteration  4: sum of abs. weighted deviations =  1210.9955
Iteration  5: sum of abs. weighted deviations =  1120.8951
Iteration  6: sum of abs. weighted deviations =  1115.6281
Iteration  7: sum of abs. weighted deviations =  1114.1291
Iteration  8: sum of abs. weighted deviations =  1110.5213
Iteration  9: sum of abs. weighted deviations =  1109.0158
Iteration 10: sum of abs. weighted deviations =  1108.9829
Iteration 11: sum of abs. weighted deviations =  1105.3692
Iteration 12: sum of abs. weighted deviations =  1104.6973
Iteration 13: sum of abs. weighted deviations =  1099.8283
Iteration 14: sum of abs. weighted deviations =  1099.1783
```

```
Iteration 15: sum of abs. weighted deviations =  1098.8175
Iteration 16: sum of abs. weighted deviations =  1098.7744
Iteration 17: sum of abs. weighted deviations =  1098.6069
Iteration 18: sum of abs. weighted deviations =  1098.5889
Iteration 19: sum of abs. weighted deviations =   1098.581
Iteration 20: sum of abs. weighted deviations =  1098.5809

.25 Quantile regression                            Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 1098.581                   Pseudo R2     =    0.1268

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0006759   .0000609    11.10   0.000     .0005565    .0007953
      fcukor |   .0004858   .0006936     0.70   0.484    -.0008743     .001846
     nfcukor |  -.0303405   .0019934   -15.22   0.000    -.0342493   -.0264316
       _cons |   6.685655   .0413198   161.80   0.000     6.604633    6.766677
------------------------------------------------------------------------------

. estimates store R33

.
. qreg logp kor, quantile(25)
Iteration  1:  WLS sum of weighted deviations =  1266.8783

Iteration  1: sum of abs. weighted deviations =  1267.2291
note:  alternate solutions exist
Iteration  2: sum of abs. weighted deviations =  1190.9132
Iteration  3: sum of abs. weighted deviations =  1103.2734
Iteration  4: sum of abs. weighted deviations =  1103.2734

.25 Quantile regression                            Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 1103.273                   Pseudo R2     =    0.1231

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         kor |   .2129577   .0149108    14.28   0.000     .1837198    .2421957
       _cons |   6.531101   .0464222   140.69   0.000     6.440074    6.622129
------------------------------------------------------------------------------

. estimates store R34

.
. qreg logp logq, quantile(25)
Iteration  1:  WLS sum of weighted deviations =   1255.931

Iteration  1: sum of abs. weighted deviations =  1256.9568
Iteration  2: sum of abs. weighted deviations =  1126.6209
Iteration  3: sum of abs. weighted deviations =   990.6536
Iteration  4: sum of abs. weighted deviations =  987.78514
Iteration  5: sum of abs. weighted deviations =  987.56994
Iteration  6: sum of abs. weighted deviations =  987.36063

.25 Quantile regression                            Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 987.3606                   Pseudo R2     =    0.2152

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.3080126   .0108171   -28.47   0.000    -.3292233   -.2868019
       _cons |   9.794381   .0977441   100.20   0.000      9.60272    9.986043
------------------------------------------------------------------------------

. estimates store R35

.
. qreg logp vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(25)
Iteration  1:  WLS sum of weighted deviations =  1425.4636

Iteration  1: sum of abs. weighted deviations =  1428.2775
Iteration  2: sum of abs. weighted deviations =  1328.0955
Iteration  3: sum of abs. weighted deviations =  1272.4029
Iteration  4: sum of abs. weighted deviations =  1242.6916
```

```
Iteration  5: sum of abs. weighted deviations =  1234.2625
Iteration  6: sum of abs. weighted deviations =  1226.1153
Iteration  7: sum of abs. weighted deviations =  1213.7095
Iteration  8: sum of abs. weighted deviations =  1211.5446
Iteration  9: sum of abs. weighted deviations =  1203.5891

.25 Quantile regression                           Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 1203.589                  Pseudo R2     =    0.0434

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      vbordo |   .3367581   .0473514     7.11   0.000      .243909    .4296073
      vegyeb |   .1398921   .0475935     2.94   0.003     .0465681    .2332161
        vnem |  -1.110697   .0888746   -12.50   0.000    -1.284968    -.936427
      ffajta |   .1957445    .042551     4.60   0.000     .1123082    .2791808
        fnem |  -.9959583   .0954378   -10.44   0.000    -1.183098   -.8088186
   muskegyeb |  -1.38e-14   .0650293    -0.00   1.000     -.127513     .127513
        csfi |  -.2233939   .0706575    -3.16   0.002     -.361943   -.0848448
       _cons |   6.906755    .036645   188.48   0.000       6.8349     6.97861
------------------------------------------------------------------------------

.
end of do-file

. do "C:\Users\peter\AppData\Local\Temp\STD00000000.tmp"

. *4 - qreg 0.5
.
. qreg logp tier1 tier2, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  1509.8101

Iteration  1: sum of abs. weighted deviations =  1509.7235
Iteration  2: sum of abs. weighted deviations =  1504.5379
note:  alternate solutions exist
Iteration  3: sum of abs. weighted deviations =   1499.682
Iteration  4: sum of abs. weighted deviations =  1499.5546

Median regression                                 Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 1499.555                  Pseudo R2     =    0.0462

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tier1 |   .3043213   .0296159    10.28   0.000     .2462488    .3623938
       tier2 |   .3896813   .0283651    13.74   0.000     .3340614    .4453012
       _cons |   7.306531   .0133879   545.75   0.000      7.28028    7.332783
------------------------------------------------------------------------------

. estimates store R42

.
. qreg logp cme2 fcukor nfcukor, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  1328.1544

Iteration  1: sum of abs. weighted deviations =  1327.4168
Iteration  2: sum of abs. weighted deviations =  1326.1953
Iteration  3: sum of abs. weighted deviations =  1325.3843
Iteration  4: sum of abs. weighted deviations =  1323.5691
Iteration  5: sum of abs. weighted deviations =  1322.3912
Iteration  6: sum of abs. weighted deviations =  1322.0706
Iteration  7: sum of abs. weighted deviations =   1321.764
Iteration  8: sum of abs. weighted deviations =  1321.6621
Iteration  9: sum of abs. weighted deviations =   1321.658
Iteration 10: sum of abs. weighted deviations =   1321.658
Iteration 11: sum of abs. weighted deviations =  1321.6576
Iteration 12: sum of abs. weighted deviations =  1321.6575
Iteration 13: sum of abs. weighted deviations =  1321.6575

Median regression                                 Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 1321.658                  Pseudo R2     =    0.1593

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
        cme2 |   .0008234   .0000345    23.88   0.000     .0007558     .000891
      fcukor |   .0006994   .0005132     1.36   0.173    -.0003069    .0017057
     nfcukor |  -.0311617   .0016234   -19.19   0.000     -.034345   -.0279783
       _cons |   6.967106   .0232627   299.50   0.000     6.921491    7.012721
------------------------------------------------------------------------------

. estimates store R43

.
. qreg logp kor, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  1308.0574

Iteration  1: sum of abs. weighted deviations =  1308.2837
note:  alternate solutions exist
Iteration  2: sum of abs. weighted deviations =   1300.592
Iteration  3: sum of abs. weighted deviations =  1299.3836
Iteration  4: sum of abs. weighted deviations =  1299.0396
Iteration  5: sum of abs. weighted deviations =   1299.039

Median regression                                    Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 1299.039                     Pseudo R2     =    0.1737

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         kor |   .2245122   .0080219    27.99   0.000     .2087824     .240242
       _cons |   6.945608   .0255452   271.90   0.000     6.895517    6.995698
------------------------------------------------------------------------------

. estimates store R44

.
. qreg logp logq, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  1326.7127

Iteration  1: sum of abs. weighted deviations =  1326.7556
Iteration  2: sum of abs. weighted deviations =  1325.9802
Iteration  3: sum of abs. weighted deviations =  1317.3375
Iteration  4: sum of abs. weighted deviations =  1317.3355
Iteration  5: sum of abs. weighted deviations =  1317.3351
Iteration  6: sum of abs. weighted deviations =   1317.335

Median regression                                    Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 1317.335                     Pseudo R2     =    0.1621

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2967889   .0088988   -33.35   0.000    -.3142382   -.2793396
       _cons |   10.05406    .080544   124.83   0.000      9.89613      10.212
------------------------------------------------------------------------------

. estimates store R45

.
. qreg logp vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  1508.3026

Iteration  1: sum of abs. weighted deviations =  1508.6844
Iteration  2: sum of abs. weighted deviations =  1502.1384
Iteration  3: sum of abs. weighted deviations =  1497.1922
Iteration  4: sum of abs. weighted deviations =  1496.5273
Iteration  5: sum of abs. weighted deviations =  1496.1147
Iteration  6: sum of abs. weighted deviations =  1496.1056
Iteration  7: sum of abs. weighted deviations =   1495.426
Iteration  8: sum of abs. weighted deviations =  1495.3196

Median regression                                    Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations  1495.32                     Pseudo R2     =    0.0489

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
      vbordo |   .4695487   .0450108    10.43   0.000     .3812891    .5578083
      vegyeb |   .2693329   .0450308     5.98   0.000      .181034    .3576318
        vnem |  -3.38e-14   .0834751    -0.00   1.000    -.1636825    .1636825
      ffajta |   .2693329    .040325     6.68   0.000     .1902613    .3484044
        fnem |   -.003643   .0923844    -0.04   0.969    -.1847954    .1775094
   muskegyeb |   .0392203   .0636696     0.62   0.538    -.0856266    .1640672
        csfi |  -.2231436   .0677884    -3.29   0.001    -.3560669   -.0902203
       _cons |   7.226209    .034923   206.92   0.000      7.15773    7.294688
------------------------------------------------------------------------------

.
end of do-file

. do "C:\Users\peter\AppData\Local\Temp\STD00000000.tmp"

. *5 - qreg 0.75
.
. qreg logp tier1 tier2, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1461.4951

Iteration  1: sum of abs. weighted deviations =  1465.5003
Iteration  2: sum of abs. weighted deviations =  1357.1066
Iteration  3: sum of abs. weighted deviations =  1336.1401
Iteration  4: sum of abs. weighted deviations =  1314.9588

.75 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 1314.959                    Pseudo R2     =    0.0408

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tier1 |   .4732952   .0651403     7.27   0.000     .3455647    .6010257
       tier2 |   .5012302   .0624238     8.03   0.000     .3788262    .6236342
       _cons |   7.695758    .029481   261.04   0.000      7.63795    7.753566
------------------------------------------------------------------------------

. estimates store R52

.
. qreg logp cme2 fcukor nfcukor, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1267.4848

Iteration  1: sum of abs. weighted deviations =  1274.7525
Iteration  2: sum of abs. weighted deviations =   1243.063
Iteration  3: sum of abs. weighted deviations =  1230.1266
Iteration  4: sum of abs. weighted deviations =  1181.7425
Iteration  5: sum of abs. weighted deviations =  1163.2422
Iteration  6: sum of abs. weighted deviations =  1123.8559
Iteration  7: sum of abs. weighted deviations =  1079.6398
Iteration  8: sum of abs. weighted deviations =  1078.0066
Iteration  9: sum of abs. weighted deviations =  1077.4816
Iteration 10: sum of abs. weighted deviations =  1075.3785
Iteration 11: sum of abs. weighted deviations =  1074.3236
Iteration 12: sum of abs. weighted deviations =  1073.8689
Iteration 13: sum of abs. weighted deviations =  1072.7953
Iteration 14: sum of abs. weighted deviations =  1072.7819
Iteration 15: sum of abs. weighted deviations =  1072.6847
Iteration 16: sum of abs. weighted deviations =  1072.6594
Iteration 17: sum of abs. weighted deviations =  1072.6546
Iteration 18: sum of abs. weighted deviations =  1072.6538

.75 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 1072.654                    Pseudo R2     =    0.2176

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0011007   .0000446    24.70   0.000     .0010134    .0011881
      fcukor |   .0005139   .0007758     0.66   0.508    -.0010072    .0020351
     nfcukor |  -.0253854   .0022741   -11.16   0.000    -.0298446   -.0209262
       _cons |   7.123713   .0281034   253.48   0.000     7.068606    7.178819
------------------------------------------------------------------------------

. estimates store R53
```

```
.
. qreg logp kor, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1252.4004

Iteration  1: sum of abs. weighted deviations =  1252.5205
Iteration  2: sum of abs. weighted deviations =  1083.1313
note:  alternate solutions exist
Iteration  3: sum of abs. weighted deviations =  1008.1712
note:  alternate solutions exist
Iteration  4: sum of abs. weighted deviations =  1008.0514
Iteration  5: sum of abs. weighted deviations =  1008.0411

.75 Quantile regression                         Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 1008.041                Pseudo R2     =    0.2647

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         kor |   .2865793    .005092    56.28   0.000     .2765946     .296564
       _cons |    7.13997   .0166101   429.86   0.000       7.1074     7.17254
------------------------------------------------------------------------------

. estimates store R54

.
. qreg logp logq, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1299.0439

Iteration  1: sum of abs. weighted deviations =  1299.5397
Iteration  2: sum of abs. weighted deviations =  1220.4446
Iteration  3: sum of abs. weighted deviations =  1168.0944
Iteration  4: sum of abs. weighted deviations =  1167.4711
Iteration  5: sum of abs. weighted deviations =  1166.1492
Iteration  6: sum of abs. weighted deviations =  1166.1464
Iteration  7: sum of abs. weighted deviations =  1166.1439
Iteration  8: sum of abs. weighted deviations =  1166.1439

.75 Quantile regression                         Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 1166.144                Pseudo R2     =    0.1494

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.3057762    .013371   -22.87   0.000    -.3319948   -.2795577
       _cons |   10.52324    .121023    86.95   0.000     10.28593    10.76055
------------------------------------------------------------------------------

. estimates store R55

.
. qreg logp vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1446.1429

Iteration  1: sum of abs. weighted deviations =  1457.1834
Iteration  2: sum of abs. weighted deviations =  1409.9175
Iteration  3: sum of abs. weighted deviations =  1357.3668
Iteration  4: sum of abs. weighted deviations =  1321.7274
Iteration  5: sum of abs. weighted deviations =  1273.4067
Iteration  6: sum of abs. weighted deviations =  1265.9969
Iteration  7: sum of abs. weighted deviations =  1259.7699
Iteration  8: sum of abs. weighted deviations =  1247.7223
Iteration  9: sum of abs. weighted deviations =  1241.9803

.75 Quantile regression                         Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations  1241.98                Pseudo R2     =    0.0941

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      vbordo |   .8254986   .0413187    19.98   0.000     .7444786    .9065185
      vegyeb |   .6180711   .0412653    14.98   0.000     .5371558    .6989864
        vnem |   .4241571   .0767879     5.52   0.000     .2735871    .5747272
      ffajta |   .6281891    .037057    16.95   0.000     .5555258    .7008524
        fnem |   .5975223   .0845268     7.07   0.000     .4317774    .7632671
```

```
   muskegyeb |   .2033257   .0585616     3.47   0.001     .0884949    .3181566
        csfi |  -.1279764   .0610063    -2.10   0.036     -.247601   -.0083519
       _cons |    7.37149   .0320984   229.65   0.000     7.308549     7.43443
------------------------------------------------------------------------------

.
end of do-file

. do "C:\Users\peter\AppData\Local\Temp\STD00000000.tmp"

. *6 - qreg 0.90

.
. qreg logp tier1 tier2, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1368.5366

Iteration  1: sum of abs. weighted deviations =  1376.3059
Iteration  2: sum of abs. weighted deviations =  983.52019
Iteration  3: sum of abs. weighted deviations =  894.22323
Iteration  4: sum of abs. weighted deviations =  802.29208

.9 Quantile regression                             Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 802.2921                   Pseudo R2     =    0.0435

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       tier1 |    .669157   .0633146    10.57   0.000     .5450064    .7933077
       tier2 |   .4677238    .062071     7.54   0.000     .3460118    .5894359
       _cons |   8.225101   .0293353   280.38   0.000     8.167579    8.282624
------------------------------------------------------------------------------

. estimates store R62

.
. qreg logp cme2 fcukor nfcukor, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1179.6103

Iteration  1: sum of abs. weighted deviations =  1214.8766
Iteration  2: sum of abs. weighted deviations =  1106.6026
Iteration  3: sum of abs. weighted deviations =  1043.8387
Iteration  4: sum of abs. weighted deviations =  959.23924
Iteration  5: sum of abs. weighted deviations =  626.74017
Iteration  6: sum of abs. weighted deviations =  626.36863
Iteration  7: sum of abs. weighted deviations =  624.31858
Iteration  8: sum of abs. weighted deviations =  622.42126
Iteration  9: sum of abs. weighted deviations =  621.34012
Iteration 10: sum of abs. weighted deviations =  621.22608
Iteration 11: sum of abs. weighted deviations =  620.98716
Iteration 12: sum of abs. weighted deviations =  620.98483
Iteration 13: sum of abs. weighted deviations =   620.6505
Iteration 14: sum of abs. weighted deviations =  620.64252
Iteration 15: sum of abs. weighted deviations =  620.64136

.9 Quantile regression                             Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 620.6414                   Pseudo R2     =    0.2601

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0012882   .0000751    17.15   0.000     .0011409    .0014355
      fcukor |   .0003786   .0013441     0.28   0.778    -.0022571    .0030142
     nfcukor |  -.0232617   .0039694    -5.86   0.000    -.0310451   -.0154784
       _cons |    7.43579   .0461991   160.95   0.000       7.3452     7.52638
------------------------------------------------------------------------------

. estimates store R63

.
. qreg logp kor, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1171.3056

Iteration  1: sum of abs. weighted deviations =  1168.3063
Iteration  2: sum of abs. weighted deviations =  794.97684
Iteration  3: sum of abs. weighted deviations =  765.50877
Iteration  4: sum of abs. weighted deviations =  603.44227
```

```
Iteration  5: sum of abs. weighted deviations =  575.22279
Iteration  6: sum of abs. weighted deviations =  572.74118
note:  alternate solutions exist
Iteration  7: sum of abs. weighted deviations =  572.55716
Iteration  8: sum of abs. weighted deviations =   572.4234
Iteration  9: sum of abs. weighted deviations =   572.3376
Iteration 10: sum of abs. weighted deviations =  572.33235

.9 Quantile regression                               Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 572.3323                     Pseudo R2     =    0.3177

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         kor |   .3499389   .0105444    33.19   0.000     .3292629    .3706148
       _cons |   7.327925   .0345729   211.96   0.000     7.260132    7.395717
------------------------------------------------------------------------------

. estimates store R64

.
. qreg logp logq, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1234.4252

Iteration  1: sum of abs. weighted deviations =   1237.125
Iteration  2: sum of abs. weighted deviations =   1159.341
Iteration  3: sum of abs. weighted deviations =  1047.4098
Iteration  4: sum of abs. weighted deviations =  786.88861
Iteration  5: sum of abs. weighted deviations =  747.68011
Iteration  6: sum of abs. weighted deviations =  747.58488
Iteration  7: sum of abs. weighted deviations =   747.5833
Iteration  8: sum of abs. weighted deviations =  747.57993
Iteration  9: sum of abs. weighted deviations =  747.57993

.9 Quantile regression                               Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 747.5799                     Pseudo R2     =    0.1087

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.3563793   .0224789   -15.85   0.000    -.4004572   -.3123015
       _cons |   11.47931   .2036197    56.38   0.000     11.08005    11.87858
------------------------------------------------------------------------------

. estimates store R65

.
. qreg logp vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1338.1563

Iteration  1: sum of abs. weighted deviations =    1351.93
Iteration  2: sum of abs. weighted deviations =   1158.316
Iteration  3: sum of abs. weighted deviations =  1020.7173
Iteration  4: sum of abs. weighted deviations =  891.09653
Iteration  5: sum of abs. weighted deviations =  824.24195
Iteration  6: sum of abs. weighted deviations =  802.70433
Iteration  7: sum of abs. weighted deviations =  792.91479
Iteration  8: sum of abs. weighted deviations =  768.31821
Iteration  9: sum of abs. weighted deviations =  748.41619

.9 Quantile regression                               Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 748.4162                     Pseudo R2     =    0.1077

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      vbordo |   1.204528   .0979096    12.30   0.000     1.012542    1.396515
      vegyeb |   .8641486   .0976057     8.85   0.000      .672758    1.055539
        vnem |   .9056735   .1748778     5.18   0.000     .5627635    1.248583
      ffajta |   1.093318   .0871622    12.54   0.000     .9224051     1.26423
        fnem |   1.179211   .1982696     5.95   0.000     .7904333    1.567989
   muskegyeb |   .5113816    .139157     3.67   0.000     .2385149    .7842483
        csfi |  -.0625024   .1489655    -0.42   0.675    -.3546021    .2295973
       _cons |   7.494986   .0749671    99.98   0.000     7.347986    7.641986
```

```
------------------------------------------------------------------------------

.
```

3. Models A1.1-7

```
. *Ekorl
. reg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm hb
kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj toln
> a villany zala, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 28,  2643) =   44.62
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2950
                                                       Root MSE      =  .67852

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .8540602   .1235146     6.91   0.000     .6118652    1.096255
     balaton |   .3526544   .1211265     2.91   0.004      .115142    .5901667
          bb |    .572901   .1137443     5.04   0.000     .3498641     .795938
       bfelv |   .5539258   .1176331     4.71   0.000     .3232636     .784588
        bfcs |    .707812   .1127183     6.28   0.000     .4867871    .9288369
        bukk |    .674426   .2124307     3.17   0.002     .2578788    1.090973
        duna |   .4598806   .2054932     2.24   0.025     .0569368    .8628243
   dunantuli |   .0775705   .1263619     0.61   0.539    -.1702078    .3253487
         dtk |  -.7892762   .1170369    -6.74   0.000    -1.018769   -.559783
        eger |   .7298416    .118636     6.15   0.000     .4972129    .9624704
   etyekbuda |   .5055251   .1214284     4.16   0.000     .2674207    .7436295
          fm |   .4133921   .1225744     3.37   0.001     .1730407    .6537436
          hb |   .2745229   .1236627     2.22   0.027     .0320374    .5170083
        kali |   1.275819    .228898     5.57   0.000      .826982    1.724657
      kunsag |   .2976394    .112219     2.65   0.008     .0775936    .5176853
       matra |   .2229573   .1135785     1.96   0.050     .0002454    .4456691
         mor |   .4745102   .1184267     4.01   0.000     .2422918    .7067287
      nsomlo |   .8569149    .131331     6.52   0.000      .599393    1.114437
    neszmely |   .5127785   .1269943     4.04   0.000     .2637602    .7617968
      pannon |   .3223611   .1161002     2.78   0.006     .0947046    .5500175
      phalma |     .73695   .1309111     5.63   0.000     .4802514    .9936487
        pecs |   .5769329   .1209691     4.77   0.000     .3397292    .8141366
      sopron |   .9229731   .1209378     7.63   0.000     .6858309    1.160115
   szekszard |   .7760449   .1085825     7.15   0.000     .5631296    .9889603
       tokaj |   1.318396   .1175316    11.22   0.000     1.087933    1.548859
       tolna |   .3603183   .1483975     2.43   0.015     .0693313    .6513053
     villany |   .8628363   .1096275     7.87   0.000     .6478718    1.077801
        zala |   .5609949   .1451103     3.87   0.000     .2764535    .8455362
       _cons |    6.83114   .1036659    65.90   0.000     6.627866    7.034415
------------------------------------------------------------------------------

. estimates store Ekorl

.
. *Ekoztl +dulo
. reg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm hb
kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj toln
> a villany zala dulo, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 29,  2642) =   52.75
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3285
                                                       Root MSE      =   .6623

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .8540602    .123538     6.91   0.000     .6118193    1.096301
     balaton |   .3526544   .1211494     2.91   0.004      .115097    .5902117
          bb |   .5178599   .1130466     4.58   0.000     .2961911    .7395287
       bfelv |   .5539258   .1176553     4.71   0.000     .3232199    .7846317
```

```
        bfcs |   .6508887   .1121031     5.81   0.000     .4310699    .8707075
        bukk |    .674426   .2124709     3.17   0.002     .2577999    1.091052
        duna |   .4598806   .2055321     2.24   0.025     .0568605    .8629006
   dunantuli |   .0775705   .1263858     0.61   0.539    -.1702547    .3253956
         dtk |  -.7892762   .1170591    -6.74   0.000    -1.018813   -.5597396
        eger |   .6539697   .1167392     5.60   0.000     .4250602    .8828792
   etyekbuda |   .4937739   .1210324     4.08   0.000      .256446    .7311018
          fm |   .3997855   .1223042     3.27   0.001     .1599637    .6396072
          hb |   .2745229   .1236861     2.22   0.027     .0319915    .5170542
        kali |   1.275819   .2289413     5.57   0.000      .826897    1.724742
      kunsag |   .2893886   .1124796     2.57   0.010     .0688317    .5099455
       matra |   .2229573      .1136     1.96   0.050     .0002033    .4457113
         mor |   .4745102   .1184491     4.01   0.000     .2422478    .7067726
      nsomlo |   .8569149   .1313558     6.52   0.000     .5993442    1.114486
    neszmely |   .4422713   .1198232     3.69   0.000     .2073145     .677228
      pannon |   .3223611   .1161221     2.78   0.006     .0946615    .5500606
      phalma |     .73695   .1309359     5.63   0.000     .4802028    .9936973
        pecs |   .5769329    .120992     4.77   0.000     .3396842    .8141815
      sopron |   .8998215   .1192051     7.55   0.000     .6660767    1.133566
   szekszard |   .7463102   .1083091     6.89   0.000     .5339311    .9586894
       tokaj |   1.241962   .1177289    10.55   0.000     1.011112    1.472812
       tolna |   .3603183   .1484256     2.43   0.015     .0692762    .6513604
     villany |   .8380837   .1093312     7.67   0.000     .6237004    1.052467
        zala |   .5609949   .1451378     3.87   0.000     .2763996    .8455901
        dulo |   .7755797   .0610601    12.70   0.000     .6558492    .8953101
       _cons |    6.83114   .1036855    65.88   0.000     6.627827    7.034453
------------------------------------------------------------------------------

. estimates store Ekozt1

.
. *Ekozt2 +egyéni márkák
. reg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eger etyekbuda fm hb
kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron szekszard tokaj toln
> a villany zala dulo tier1 tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 31,  2640) =   59.92
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3733
                                                       Root MSE      =  .64007

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .7372209   .1188947     6.20   0.000     .5040848    .9703571
     balaton |   .3420042   .1136292     3.01   0.003     .1191929    .5648155
          bb |   .4615487   .1062727     4.34   0.000     .2531625    .6699349
       bfelv |   .5691123   .1128748     5.04   0.000     .3477803    .7904444
        bfcs |   .5538776   .1086507     5.10   0.000     .3408285    .7669267
        bukk |    .733775   .2091495     3.51   0.000     .3236615    1.143888
        duna |   .5192296   .2020912     2.57   0.010     .1229564    .9155027
   dunantuli |   .0256847   .1168277     0.22   0.826    -.2033985    .2547678
         dtk |  -.7450685   .1094453    -6.81   0.000    -.9596757   -.5304613
        eger |    .583907   .1089821     5.36   0.000      .370208     .797606
   etyekbuda |   .4545961    .115339     3.94   0.000     .2284322    .6807601
          fm |   .3378986   .1153622     2.93   0.003     .1116892     .564108
          hb |   .3338718   .1177933     2.83   0.005     .1028953    .5648483
        kali |   1.335168   .2258745     5.91   0.000     .8922595    1.778077
      kunsag |     .24466   .1068841     2.29   0.022      .035075    .4542451
       matra |   .1941183   .1051657     1.85   0.065    -.0120972    .4003339
         mor |   .5052881   .1068984     4.73   0.000     .2956751    .7149012
      nsomlo |   .8255948    .120558     6.85   0.000     .5891971    1.061993
    neszmely |   .1882848   .1188786     1.58   0.113    -.0448198    .4213894
      pannon |   .2988787   .1068861     2.80   0.005     .0892897    .5084677
      phalma |   .5702149   .1232522     4.63   0.000     .3285341    .8118956
        pecs |   .6284589   .1151792     5.46   0.000     .4026083    .8543095
      sopron |   .7703263   .1089943     7.07   0.000     .5566034    .9840492
   szekszard |   .6508273    .101616     6.40   0.000     .4515722    .8500824
       tokaj |   1.153478   .1111525    10.38   0.000     .9355228    1.371433
       tolna |   .4086663   .1430971     2.86   0.004     .1280724    .6892601
     villany |   .7005433   .1022564     6.85   0.000     .5000325    .9010541
        zala |   .2340522   .1469099     1.59   0.111    -.0540179    .5221223
        dulo |   .7019382   .0593208    11.83   0.000     .5856182    .8182581
       tier1 |   .3520332    .039531     8.91   0.000     .2745183     .429548
       tier2 |    .399995   .0345483    11.58   0.000     .3322505    .4677396
```

```
       _cons |   6.771791   .0965622    70.13   0.000     6.582446    6.961137
------------------------------------------------------------------------------

. estimates store Ekozt2

.
. *Ekozt3 +beltartalom
. reg logp cme2 fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna dunantul dtk
eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron
> szekszard tokaj tolna villany zala dulo tier1 tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 34,  2637) =   66.14
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5290
                                                       Root MSE      =   .5552

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0004499   .0001184     3.80   0.000     .0002178    .0006821
      fcukor |   .0027931   .0010224     2.73   0.006     .0007882    .0047979
     nfcukor |  -.0149501    .001793    -8.34   0.000    -.0184659   -.0114343
   badacsony |    .605169   .1141041     5.30   0.000     .3814264    .8289116
     balaton |   .3113983   .1047299     2.97   0.003     .1060373    .5167593
          bb |   .3250771   .0987579     3.29   0.001     .1314264    .5187278
       bfelv |   .4163705   .1073993     3.88   0.000      .205775     .626966
        bfcs |   .4451003    .101851     4.37   0.000     .2453844    .6448162
        bukk |   .6642223   .1989191     3.34   0.001     .2741689    1.054276
        duna |   .3402454   .1844908     1.84   0.065    -.0215158    .7020067
   dunantuli |   .0052201   .1078691     0.05   0.961    -.2062967    .2167368
         dtk |  -.7899888   .1049631    -7.53   0.000    -.9958071   -.5841704
        eger |   .4138785   .1048121     3.95   0.000     .2083562    .6194008
   etyekbuda |   .3686588   .1096939     3.36   0.001      .153564    .5837535
          fm |   .2953259   .1058963     2.79   0.005     .0876775    .5029742
          hb |   .1337577   .1111523     1.20   0.229    -.0841968    .3517121
        kali |   1.101376   .1857034     5.93   0.000     .7372372    1.465515
      kunsag |   .1061312   .0984646     1.08   0.281    -.0869445    .2992069
       matra |   .0991427   .0986036     1.01   0.315    -.0942057     .292491
         mor |   .4250096   .1034177     4.11   0.000     .2222215    .6277978
      nsomlo |   .6746196   .1180918     5.71   0.000     .4430576    .9061816
    neszmely |   .1093478   .1117251     0.98   0.328    -.1097298    .3284255
      pannon |   .2114263   .1018206     2.08   0.038       .01177    .4110826
      phalma |   .5201369   .1150923     4.52   0.000     .2944567    .7458172
        pecs |   .4604935   .1037229     4.44   0.000     .2571071    .6638799
      sopron |   .6573693   .1026334     6.41   0.000     .4561191    .8586195
   szekszard |   .4745095   .0986232     4.81   0.000     .2811228    .6678961
       tokaj |   .5549918   .1036017     5.36   0.000      .351843    .7581405
       tolna |   .2726999   .1312234     2.08   0.038     .0153886    .5300112
     villany |   .5271294   .0989657     5.33   0.000     .3330711    .7211878
        zala |   .1531518   .1328556     1.15   0.249    -.1073599    .4136636
        dulo |   .8135659   .0539763    15.07   0.000     .7077257    .9194061
       tier1 |   .3181725    .033042     9.63   0.000     .2533817    .3829634
       tier2 |   .3258547    .028666    11.37   0.000     .2696447    .3820647
       _cons |    6.65714   .1089521    61.10   0.000       6.4435    6.870781
------------------------------------------------------------------------------

. estimates store Ekozt3

.
. *Ekozt4 +kor
. reg logp cme2 fcukor nfcukor kor badacsony balaton bb bfelv bfcs bukk duna dunantul
dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sop
> ron szekszard tokaj tolna villany zala dulo tier1 tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 35,  2636) =   91.36
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6223
                                                       Root MSE      =  .49727

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0002295   .0000609     3.77   0.000     .0001102    .0003489
```

```
      fcukor |   .0026287   .0006914     3.80   0.000      .001273    .0039843
     nfcukor |  -.0130286   .0015083    -8.64   0.000     -.015986   -.0100711
         kor |   .1557975   .0083307    18.70   0.000     .1394621     .172133
   badacsony |   .5391278   .1045215     5.16   0.000     .3341753    .7440803
     balaton |   .3677418   .0966997     3.80   0.000     .1781267    .5573569
          bb |   .3358827   .0865551     3.88   0.000     .1661599    .5056054
       bfelv |   .5607669   .1004968     5.58   0.000     .3637062    .7578276
        bfcs |   .5100647   .0891179     5.72   0.000     .3353166    .6848128
        bukk |   .7403609   .1836795     4.03   0.000     .3801902    1.100532
        duna |    .373866   .1430161     2.61   0.009     .0934308    .6543013
   dunantuli |    .122127   .0978289     1.25   0.212    -.0697023    .3139563
         dtk |  -.6460008   .0949638    -6.80   0.000    -.8322119   -.4597897
        eger |   .2731038   .0902614     3.03   0.003     .0961133    .4500942
   etyekbuda |   .4145722   .0960662     4.32   0.000     .2261993     .602945
          fm |   .3282731   .0922011     3.56   0.000     .1474792     .509067
          hb |   .1418664   .1013872     1.40   0.162    -.0569401    .3406729
        kali |    1.07792   .1491697     7.23   0.000     .7854187    1.370422
      kunsag |    .151358   .0884432     1.71   0.087    -.0220671    .3247832
       matra |   .1392407   .0875923     1.59   0.112    -.0325159    .3109973
         mor |   .5533688   .0959053     5.77   0.000     .3653115     .741426
      nsomlo |   .6381578   .1158723     5.51   0.000     .4109479    .8653676
    neszmely |   .2232351   .1017292     2.19   0.028      .023758    .4227122
      pannon |   .3348691   .0993496     3.37   0.001     .1400581    .5296801
      phalma |   .6988089   .1076913     6.49   0.000     .4876409    .9099768
        pecs |   .4830978   .0891642     5.42   0.000      .308259    .6579367
      sopron |   .6685645   .0886963     7.54   0.000     .4946431    .8424859
   szekszard |   .4403645   .0843851     5.22   0.000     .2748967    .6058323
       tokaj |     .46878   .0907577     5.17   0.000     .2908166    .6467434
       tolna |   .2033114   .1098305     1.85   0.064    -.0120514    .4186742
     villany |   .4904778   .0844727     5.81   0.000     .3248383    .6561173
        zala |   .1981385   .0978491     2.02   0.043     .0062698    .3900073
        dulo |   .6556715   .0560454    11.70   0.000      .545774     .765569
       tier1 |   .2876929   .0285666    10.07   0.000     .2316777    .3437082
       tier2 |   .2889895   .0260711    11.08   0.000     .2378676    .3401113
       _cons |   6.438975   .0844508    76.25   0.000     6.273378    6.604571
------------------------------------------------------------------------------

. estimates store Ekozt4

.
. *Ekozt5 +mennyiseg
. reg logp logq cme2 fcukor nfcukor kor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pec
> s sopron szekszard tokaj tolna villany zala dulo tier1 tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 36,  2635) =  170.34
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7395
                                                       Root MSE      =  .41306

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |    -.22797   .0068584   -33.24   0.000    -.2414185   -.2145216
        cme2 |   .0001828   .0000577     3.17   0.002     .0000696     .000296
      fcukor |   .0025898   .0006104     4.24   0.000     .0013929    .0037866
     nfcukor |  -.0058396   .0011762    -4.96   0.000     -.008146   -.0035331
         kor |   .1353602   .0073792    18.34   0.000     .1208906    .1498298
   badacsony |   .3000023   .0777834     3.86   0.000     .1474796     .452525
     balaton |   .3532439   .0693627     5.09   0.000     .2172331    .4892547
          bb |   .2766531   .0672477     4.11   0.000     .1447894    .4085168
       bfelv |   .2665255   .0811065     3.29   0.001     .1074866    .4255644
        bfcs |   .3041877   .0670949     4.53   0.000     .1726238    .4357517
        bukk |   .2269255     .17227     1.32   0.188    -.1108727    .5647236
        duna |   .1110957   .1583893     0.70   0.483    -.1994843    .4216757
   dunantuli |   .1864615   .0707001     2.64   0.008     .0478282    .3250947
         dtk |  -.4429769    .069619    -6.36   0.000    -.5794904   -.3064634
        eger |   .3217437   .0673589     4.78   0.000      .189662    .4538254
   etyekbuda |   .3614889   .0707745     5.11   0.000     .2227096    .5002682
          fm |   .2026791   .0682271     2.97   0.003      .068895    .3364632
          hb |   .1255915   .0910547     1.38   0.168    -.0529545    .3041375
        kali |   .8270243   .1623992     5.09   0.000     .5085815    1.145467
      kunsag |  -.0338601   .0699882    -0.48   0.629    -.1710974    .1033772
       matra |    .019508   .0635617     0.31   0.759     -.105128     .144144
```

```
         mor |   .2701961   .0722148     3.74   0.000     .1285926    .4117996
      nsomlo |   .3719091   .0892381     4.17   0.000     .1969252     .546893
    neszmely |   .1813884   .0794117     2.28   0.022     .0256727     .337104
      pannon |    .333145   .0955999     3.48   0.001     .1456865    .5206035
      phalma |   .5575076   .0923619     6.04   0.000     .3763985    .7386168
        pecs |   .2468925   .0763386     3.23   0.001     .0972028    .3965822
      sopron |    .350182    .068444     5.12   0.000     .2159727    .4843914
   szekszard |   .3280495   .0631797     5.19   0.000     .2041626    .4519364
       tokaj |   .3621073   .0688528     5.26   0.000     .2270963    .4971184
       tolna |   .0528532   .0937618     0.56   0.573     -.131001    .2367073
     villany |   .4384093    .062928     6.97   0.000      .315016    .5618027
        zala |  -.0211166   .0775418    -0.27   0.785    -.1731657    .1309324
        dulo |   .4145286    .049071     8.45   0.000      .318307    .5107502
       tier1 |   .4048241   .0251652    16.09   0.000     .3554785    .4541696
       tier2 |   .2976575    .022116    13.46   0.000      .254291     .341024
       _cons |    8.62349   .0931651    92.56   0.000     8.440805    8.806174
------------------------------------------------------------------------------

. estimates store Ekozt5

.
. *Ekit (+szolofajta)
. reg logp logq cme2 fcukor nfcukor kor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pec
> s sopron szekszard tokaj tolna villany zala dulo tier1 tier2 vbordo vegyeb vnem ffajta
fnem muskegyeb csfi, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 43,  2628) =  151.71
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7453
                                                       Root MSE      =  .40901

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2295695   .0068913   -33.31   0.000    -.2430825   -.2160565
        cme2 |   .0001366    .000059     2.32   0.021     .0000209    .0002523
      fcukor |   .0033999    .000709     4.80   0.000     .0020096    .0047901
     nfcukor |  -.0068086   .0013059    -5.21   0.000    -.0093693   -.0042479
         kor |   .1309201   .0069623    18.80   0.000     .1172679    .1445724
   badacsony |   .3139697   .0792758     3.96   0.000     .1585203    .4694191
     balaton |   .3263304   .0717616     4.55   0.000     .1856154    .4670454
          bb |   .2411841   .0676091     3.57   0.000     .1086116    .3737566
       bfelv |   .2709756   .0819215     3.31   0.001     .1103383    .4316128
        bfcs |   .2860373   .0682843     4.19   0.000      .152141    .4199337
        bukk |   .2164032   .1795023     1.21   0.228    -.1355768    .5683833
        duna |   .0888709    .161734     0.55   0.583     -.228268    .4060098
   dunantuli |   .1525958   .0715537     2.13   0.033     .0122885    .2929032
         dtk |  -.4393849   .0706867    -6.22   0.000    -.5779921   -.3007777
        eger |    .319503   .0688701     4.64   0.000     .1844579    .4545481
   etyekbuda |   .3534028   .0730693     4.84   0.000     .2101237     .496682
          fm |   .1840104   .0697269     2.64   0.008     .0472852    .3207356
          hb |   .0774828   .0908113     0.85   0.394    -.1005861    .2555516
        kali |   .7889084   .1537171     5.13   0.000     .4874896    1.090327
      kunsag |  -.0592746   .0706417    -0.84   0.401    -.1977937    .0792445
       matra |  -.0042471    .064776    -0.07   0.948    -.1312642    .1227699
         mor |   .2717174   .0721633     3.77   0.000     .1302147    .4132201
      nsomlo |   .3985063   .0908246     4.39   0.000     .2204114    .5766012
    neszmely |   .1767229   .0806228     2.19   0.028     .0186324    .3348135
      pannon |    .281694   .0983088     2.87   0.004     .0889235    .4744645
      phalma |   .5333819   .0938816     5.68   0.000     .3492924    .7174713
        pecs |   .2309363   .0780776     2.96   0.003     .0778365     .384036
      sopron |   .3168625   .0706078     4.49   0.000       .17841    .4553151
   szekszard |   .2791665   .0644742     4.33   0.000     .1527412    .4055919
       tokaj |   .3734884   .0703488     5.31   0.000     .2355437    .5114331
       tolna |   .0174664   .0957449     0.18   0.855    -.1702766    .2052094
     villany |   .3891644   .0640718     6.07   0.000     .2635281    .5148007
        zala |  -.0312159   .0737916    -0.42   0.672    -.1759114    .1134795
        dulo |    .421837   .0481731     8.76   0.000      .327376     .516298
       tier1 |    .410318   .0246337    16.66   0.000     .3620147    .4586213
       tier2 |    .298209   .0221566    13.46   0.000     .2547629    .3416551
      vbordo |   .0628277   .0351769     1.79   0.074    -.0061496     .131805
      vegyeb |  -.0941638   .0318484    -2.96   0.003    -.1566142   -.0317134
        vnem |  -.1310127   .0646408    -2.03   0.043    -.2577647   -.0042607
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```
      ffajta |  -.1093079   .0238376    -4.59   0.000    -.1560503   -.0625655
        fnem |  -.1564228   .0693243    -2.26   0.024    -.2923586    -.020487
   muskegyeb |  -.1514617   .0390026    -3.88   0.000    -.2279406   -.0749829
        csfi |   -.079466   .0383826    -2.07   0.039    -.1547292   -.0042029
       _cons |   8.758141   .0961921    91.05   0.000     8.569521    8.946761
------------------------------------------------------------------------------

. estimates store Ekit
```

4. Models A2-A6

```
.
. *0,1 EGYBEN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pe
> cs sopron szekszard tokaj tolna villany zala dulo tier1 tier2 vbordo vegyeb vnem
ffajta fnem muskegyeb csfi, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  695.85634

Iteration  1: sum of abs. weighted deviations =  720.72725
Iteration  2: sum of abs. weighted deviations =  699.25059
Iteration  3: sum of abs. weighted deviations =  692.45142
Iteration  4: sum of abs. weighted deviations =  663.94085
Iteration  5: sum of abs. weighted deviations =  655.61052
Iteration  6: sum of abs. weighted deviations =  634.83861
Iteration  7: sum of abs. weighted deviations =  616.06045
Iteration  8: sum of abs. weighted deviations =  577.05033
Iteration  9: sum of abs. weighted deviations =  564.21289
Iteration 10: sum of abs. weighted deviations =  560.61493
Iteration 11: sum of abs. weighted deviations =  560.31734
Iteration 12: sum of abs. weighted deviations =  556.88415
Iteration 13: sum of abs. weighted deviations =  552.64136
Iteration 14: sum of abs. weighted deviations =  538.05023
Iteration 15: sum of abs. weighted deviations =  536.14196
Iteration 16: sum of abs. weighted deviations =  528.99957
Iteration 17: sum of abs. weighted deviations =  526.71621
Iteration 18: sum of abs. weighted deviations =  521.02954
Iteration 19: sum of abs. weighted deviations =  519.60046
Iteration 20: sum of abs. weighted deviations =  516.77914
Iteration 21: sum of abs. weighted deviations =  514.73909
Iteration 22: sum of abs. weighted deviations =  508.74291
Iteration 23: sum of abs. weighted deviations =  493.26304
Iteration 24: sum of abs. weighted deviations =  489.21759
Iteration 25: sum of abs. weighted deviations =  486.31629
Iteration 26: sum of abs. weighted deviations =  484.23644
Iteration 27: sum of abs. weighted deviations =  482.14812
Iteration 28: sum of abs. weighted deviations =  480.55784
Iteration 29: sum of abs. weighted deviations =  472.75996
Iteration 30: sum of abs. weighted deviations =  469.70484
Iteration 31: sum of abs. weighted deviations =  468.91587
Iteration 32: sum of abs. weighted deviations =  459.94091
Iteration 33: sum of abs. weighted deviations =  458.86066
Iteration 34: sum of abs. weighted deviations =  442.13722
Iteration 35: sum of abs. weighted deviations =  439.98106
Iteration 36: sum of abs. weighted deviations =  435.69502
Iteration 37: sum of abs. weighted deviations =  431.98861
Iteration 38: sum of abs. weighted deviations =  430.02557
Iteration 39: sum of abs. weighted deviations =  429.28785
Iteration 40: sum of abs. weighted deviations =   428.3574
Iteration 41: sum of abs. weighted deviations =  426.55631
Iteration 42: sum of abs. weighted deviations =  422.86114
Iteration 43: sum of abs. weighted deviations =  419.88365
Iteration 44: sum of abs. weighted deviations =  417.51656
Iteration 45: sum of abs. weighted deviations =   413.1664
Iteration 46: sum of abs. weighted deviations =  412.80025
Iteration 47: sum of abs. weighted deviations =  409.56488
Iteration 48: sum of abs. weighted deviations =  409.06158
Iteration 49: sum of abs. weighted deviations =  408.81613
Iteration 50: sum of abs. weighted deviations =  408.07703
Iteration 51: sum of abs. weighted deviations =  407.29322
Iteration 52: sum of abs. weighted deviations =  407.05749
Iteration 53: sum of abs. weighted deviations =  405.95839
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Iteration 54: sum of abs. weighted deviations =  404.49664
Iteration 55: sum of abs. weighted deviations =  404.39489
Iteration 56: sum of abs. weighted deviations =  404.06228
Iteration 57: sum of abs. weighted deviations =  404.03305
Iteration 58: sum of abs. weighted deviations =  403.21894
Iteration 59: sum of abs. weighted deviations =  402.74838
Iteration 60: sum of abs. weighted deviations =  402.31337
Iteration 61: sum of abs. weighted deviations =  402.08027
Iteration 62: sum of abs. weighted deviations =  401.48166
Iteration 63: sum of abs. weighted deviations =  400.74052
Iteration 64: sum of abs. weighted deviations =  397.26373
Iteration 65: sum of abs. weighted deviations =  396.10438
Iteration 66: sum of abs. weighted deviations =  394.92319
Iteration 67: sum of abs. weighted deviations =  394.29373
Iteration 68: sum of abs. weighted deviations =  391.18221
Iteration 69: sum of abs. weighted deviations =  390.71957
Iteration 70: sum of abs. weighted deviations =  386.72812
Iteration 71: sum of abs. weighted deviations =  386.36152
Iteration 72: sum of abs. weighted deviations =  384.90127
Iteration 73: sum of abs. weighted deviations =  384.66121
Iteration 74: sum of abs. weighted deviations =  382.92373
Iteration 75: sum of abs. weighted deviations =  382.32261
Iteration 76: sum of abs. weighted deviations =  382.25111
Iteration 77: sum of abs. weighted deviations =  380.71212
Iteration 78: sum of abs. weighted deviations =  376.04108
Iteration 79: sum of abs. weighted deviations =  376.01666
Iteration 80: sum of abs. weighted deviations =  376.01504
Iteration 81: sum of abs. weighted deviations =  375.11855
Iteration 82: sum of abs. weighted deviations =  375.09465
note:  alternate solutions exist
Iteration 83: sum of abs. weighted deviations =  374.08419
Iteration 84: sum of abs. weighted deviations =  373.08524
Iteration 85: sum of abs. weighted deviations =   372.9836
Iteration 86: sum of abs. weighted deviations =  372.61566
Iteration 87: sum of abs. weighted deviations =  371.01996
Iteration 88: sum of abs. weighted deviations =  369.25902
Iteration 89: sum of abs. weighted deviations =  369.15099
Iteration 90: sum of abs. weighted deviations =   368.8674
Iteration 91: sum of abs. weighted deviations =  368.35828
Iteration 92: sum of abs. weighted deviations =  367.73562
Iteration 93: sum of abs. weighted deviations =  367.57861
Iteration 94: sum of abs. weighted deviations =  365.79727
Iteration 95: sum of abs. weighted deviations =  365.45056
Iteration 96: sum of abs. weighted deviations =  365.38006
Iteration 97: sum of abs. weighted deviations =   365.2476
Iteration 98: sum of abs. weighted deviations =   365.2368
Iteration 99: sum of abs. weighted deviations =  365.22103
Iteration 100: sum of abs. weighted deviations =   365.2203
Iteration 101: sum of abs. weighted deviations =   365.0052
Iteration 102: sum of abs. weighted deviations =  364.93492
Iteration 103: sum of abs. weighted deviations =  364.79864
Iteration 104: sum of abs. weighted deviations =  363.41098
Iteration 105: sum of abs. weighted deviations =   363.3703
Iteration 106: sum of abs. weighted deviations =  363.34656
Iteration 107: sum of abs. weighted deviations =  362.68225
Iteration 108: sum of abs. weighted deviations =  362.52068
Iteration 109: sum of abs. weighted deviations =  362.30849
Iteration 110: sum of abs. weighted deviations =  362.20659
Iteration 111: sum of abs. weighted deviations =  362.08469
Iteration 112: sum of abs. weighted deviations =  360.87151
Iteration 113: sum of abs. weighted deviations =  360.75699
Iteration 114: sum of abs. weighted deviations =  360.11784
Iteration 115: sum of abs. weighted deviations =  360.09587
Iteration 116: sum of abs. weighted deviations =  360.02405
Iteration 117: sum of abs. weighted deviations =  359.82572
Iteration 118: sum of abs. weighted deviations =  359.77336
Iteration 119: sum of abs. weighted deviations =  359.23824
Iteration 120: sum of abs. weighted deviations =  359.08672
Iteration 121: sum of abs. weighted deviations =  358.70445
Iteration 122: sum of abs. weighted deviations =   358.5212
Iteration 123: sum of abs. weighted deviations =   358.4853
Iteration 124: sum of abs. weighted deviations =  358.29707
Iteration 125: sum of abs. weighted deviations =   358.2591
Iteration 126: sum of abs. weighted deviations =  358.18947
Iteration 127: sum of abs. weighted deviations =  358.03183
Iteration 128: sum of abs. weighted deviations =  357.93915
Iteration 129: sum of abs. weighted deviations =  357.88807
```

```
Iteration 130: sum of abs. weighted deviations =  357.84265
Iteration 131: sum of abs. weighted deviations =  356.44255
Iteration 132: sum of abs. weighted deviations =  355.73881
Iteration 133: sum of abs. weighted deviations =  355.73112
Iteration 134: sum of abs. weighted deviations =  355.70634
Iteration 135: sum of abs. weighted deviations =  355.69016
Iteration 136: sum of abs. weighted deviations =   355.6782
Iteration 137: sum of abs. weighted deviations =  355.59656
Iteration 138: sum of abs. weighted deviations =   355.5097
Iteration 139: sum of abs. weighted deviations =  355.47777
Iteration 140: sum of abs. weighted deviations =  355.46767
Iteration 141: sum of abs. weighted deviations =   355.4596
Iteration 142: sum of abs. weighted deviations =  355.18427
Iteration 143: sum of abs. weighted deviations =  354.82405
Iteration 144: sum of abs. weighted deviations =  354.81916
Iteration 145: sum of abs. weighted deviations =  354.81296
Iteration 146: sum of abs. weighted deviations =  354.79642
Iteration 147: sum of abs. weighted deviations =  354.78653
Iteration 148: sum of abs. weighted deviations =  354.77488
Iteration 149: sum of abs. weighted deviations =  354.76565
Iteration 150: sum of abs. weighted deviations =  354.75304
Iteration 151: sum of abs. weighted deviations =  354.74568
Iteration 152: sum of abs. weighted deviations =  354.73084
Iteration 153: sum of abs. weighted deviations =  354.72843
Iteration 154: sum of abs. weighted deviations =  354.72521
Iteration 155: sum of abs. weighted deviations =  354.72292
Iteration 156: sum of abs. weighted deviations =  354.71885
Iteration 157: sum of abs. weighted deviations =   354.7177
Iteration 158: sum of abs. weighted deviations =  354.68832
Iteration 159: sum of abs. weighted deviations =  354.68574
Iteration 160: sum of abs. weighted deviations =  354.68526
Iteration 161: sum of abs. weighted deviations =  354.68509
Iteration 162: sum of abs. weighted deviations =  354.68046
Iteration 163: sum of abs. weighted deviations =  354.66262
Iteration 164: sum of abs. weighted deviations =  354.66112
Iteration 165: sum of abs. weighted deviations =  354.66057
Iteration 166: sum of abs. weighted deviations =  354.65916
Iteration 167: sum of abs. weighted deviations =  354.65874
Iteration 168: sum of abs. weighted deviations =   354.6532
Iteration 169: sum of abs. weighted deviations =   354.6475
Iteration 170: sum of abs. weighted deviations =  354.63519
Iteration 171: sum of abs. weighted deviations =  354.63491
Iteration 172: sum of abs. weighted deviations =  354.63243

.1 Quantile regression                              Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations 354.6324                    Pseudo R2     =    0.5152

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2203981   .0121905   -18.08   0.000    -.2443021   -.1964941
        cme2 |   .0000919   .0000507     1.81   0.070    -7.54e-06    .0001914
         kor |   .0955304   .0097732     9.77   0.000     .0763665    .1146942
      fcukor |   .0038398   .0008009     4.79   0.000     .0022694    .0054103
     nfcukor |  -.0032066   .0019709    -1.63   0.104    -.0070713     .000658
   badacsony |   .6464154   .1133591     5.70   0.000     .4241332    .8686976
     balaton |    .599536    .114318     5.24   0.000     .3753736    .8236984
          bb |   .4735084   .0975767     4.85   0.000     .2821735    .6648433
       bfelv |   .7316518   .1552058     4.71   0.000     .4273138     1.03599
        bfcs |   .5816658   .1051672     5.53   0.000     .3754469    .7878846
        bukk |   .5738076   .1255263     4.57   0.000     .3276672    .8199479
        duna |   .3408461   .1221597     2.79   0.005     .1013071     .580385
   dunantuli |   .5361707    .111051     4.83   0.000     .3184144    .7539269
         dtk |  -.1167138   .1047096    -1.11   0.265    -.3220355    .0886078
        eger |   .5956691   .0956229     6.23   0.000     .4081653    .7831728
   etyekbuda |   .6453847    .118574     5.44   0.000     .4128768    .8778925
          fm |   .3603966   .1030322     3.50   0.000     .1583641     .562429
          hb |   .5283501   .1431012     3.69   0.000     .2477477    .8089525
        kali |    1.09415   .1245069     8.79   0.000      .850009    1.338292
      kunsag |   .3114306   .1116891     2.79   0.005     .0924231     .530438
       matra |   .4352295   .1025273     4.25   0.000      .234187     .636272
         mor |   .8496488   .1872719     4.54   0.000     .4824334    1.216864
      nsomlo |   .7066062   .1391149     5.08   0.000     .4338204     .979392
    neszmely |   .5770282   .1522926     3.79   0.000     .2784026    .8756538
      pannon |   .6701856   .1638175     4.09   0.000     .3489612      .99141
      phalma |   .9438471   .1670642     5.65   0.000     .6162565    1.271438
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        pecs |   .6662282    .121753     5.47   0.000     .4274867    .9049697
      sopron |   .7657792   .1185466     6.46   0.000      .533325    .9982334
   szekszard |   .6184055   .0920331     6.72   0.000     .4379409    .7988701
       tokaj |   .5530377   .0986914     5.60   0.000      .359517    .7465583
       tolna |   .2201162   .1501425     1.47   0.143    -.0742934    .5145257
     villany |   .7258481    .091404     7.94   0.000     .5466169    .9050793
        zala |   .5909029   .1200939     4.92   0.000     .3554147    .8263911
        dulo |   .4812597    .076892     6.26   0.000     .3304846    .6320347
       tier1 |   .4281652   .0417757    10.25   0.000     .3462487    .5100818
       tier2 |   .2910981   .0389291     7.48   0.000     .2147633    .3674329
      vbordo |   .0004715   .0618529     0.01   0.994    -.1208138    .1217568
      vegyeb |  -.1516798    .056896    -2.67   0.008    -.2632453   -.0401143
        vnem |  -.1306184   .0985786    -1.33   0.185    -.3239179    .0626811
      ffajta |  -.1306192   .0482201    -2.71   0.007    -.2251724   -.0360659
        fnem |  -.2515492   .0994624    -2.53   0.011    -.4465818   -.0565167
   muskegyeb |  -.1505802   .0738233    -2.04   0.041    -.2953379   -.0058224
        csfi |  -.1118197   .0789407    -1.42   0.157    -.2666119    .0429726
       _cons |   8.013607   .1476281    54.28   0.000     7.724128    8.303086
------------------------------------------------------------------------------

. estimates store qe10

.
. *0,25 EGYBEN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pe
> cs sopron szekszard tokaj tolna villany zala dulo tier1 tier2 vbordo vegyeb vnem
ffajta fnem muskegyeb csfi, quantile(25)
Iteration  1:  WLS sum of weighted deviations =  777.70284

Iteration  1: sum of abs. weighted deviations =   860.5078
Iteration  2: sum of abs. weighted deviations =  768.54785
Iteration  3: sum of abs. weighted deviations =  767.39158
Iteration  4: sum of abs. weighted deviations =  765.02423
Iteration  5: sum of abs. weighted deviations =  762.71673
Iteration  6: sum of abs. weighted deviations =  758.38975
Iteration  7: sum of abs. weighted deviations =  754.22291
Iteration  8: sum of abs. weighted deviations =  746.35736
Iteration  9: sum of abs. weighted deviations =  739.99735
Iteration 10: sum of abs. weighted deviations =   737.9889
Iteration 11: sum of abs. weighted deviations =   737.4932
Iteration 12: sum of abs. weighted deviations =  734.26513
Iteration 13: sum of abs. weighted deviations =  731.88154
Iteration 14: sum of abs. weighted deviations =   730.7265
Iteration 15: sum of abs. weighted deviations =  730.16578
Iteration 16: sum of abs. weighted deviations =  725.15046
Iteration 17: sum of abs. weighted deviations =   724.1843
Iteration 18: sum of abs. weighted deviations =  722.63863
Iteration 19: sum of abs. weighted deviations =  716.85047
note:  alternate solutions exist
Iteration 20: sum of abs. weighted deviations =  711.51147
Iteration 21: sum of abs. weighted deviations =  710.81353
Iteration 22: sum of abs. weighted deviations =  706.21598
Iteration 23: sum of abs. weighted deviations =  704.62384
Iteration 24: sum of abs. weighted deviations =   703.0805
Iteration 25: sum of abs. weighted deviations =  702.41365
Iteration 26: sum of abs. weighted deviations =  702.36357
Iteration 27: sum of abs. weighted deviations =  702.25172
Iteration 28: sum of abs. weighted deviations =   701.2891
Iteration 29: sum of abs. weighted deviations =  695.24448
Iteration 30: sum of abs. weighted deviations =  690.31431
Iteration 31: sum of abs. weighted deviations =  689.03775
Iteration 32: sum of abs. weighted deviations =  687.34631
Iteration 33: sum of abs. weighted deviations =  684.38995
Iteration 34: sum of abs. weighted deviations =  683.31978
Iteration 35: sum of abs. weighted deviations =  681.22497
Iteration 36: sum of abs. weighted deviations =  680.92981
Iteration 37: sum of abs. weighted deviations =  680.07709
Iteration 38: sum of abs. weighted deviations =  678.92609
Iteration 39: sum of abs. weighted deviations =  678.57462
Iteration 40: sum of abs. weighted deviations =  677.10342
Iteration 41: sum of abs. weighted deviations =   676.9441
Iteration 42: sum of abs. weighted deviations =  676.05279
Iteration 43: sum of abs. weighted deviations =  675.09807
Iteration 44: sum of abs. weighted deviations =  674.40685
Iteration 45: sum of abs. weighted deviations =   673.7221
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Iteration 46: sum of abs. weighted deviations =  673.09598
Iteration 47: sum of abs. weighted deviations =  672.70583
Iteration 48: sum of abs. weighted deviations =   671.3749
Iteration 49: sum of abs. weighted deviations =  671.21337
Iteration 50: sum of abs. weighted deviations =   670.8561
Iteration 51: sum of abs. weighted deviations =  670.46653
Iteration 52: sum of abs. weighted deviations =  670.31209
Iteration 53: sum of abs. weighted deviations =  670.19727
note:  alternate solutions exist
Iteration 54: sum of abs. weighted deviations =   667.1222
Iteration 55: sum of abs. weighted deviations =  667.02331
Iteration 56: sum of abs. weighted deviations =  666.77417
Iteration 57: sum of abs. weighted deviations =  665.79798
Iteration 58: sum of abs. weighted deviations =  665.52404
Iteration 59: sum of abs. weighted deviations =  665.28996
Iteration 60: sum of abs. weighted deviations =  665.23597
Iteration 61: sum of abs. weighted deviations =   665.0683
Iteration 62: sum of abs. weighted deviations =  665.06476
Iteration 63: sum of abs. weighted deviations =  664.95498
Iteration 64: sum of abs. weighted deviations =  664.63456
Iteration 65: sum of abs. weighted deviations =  662.26063
Iteration 66: sum of abs. weighted deviations =  661.21818
Iteration 67: sum of abs. weighted deviations =  661.01585
Iteration 68: sum of abs. weighted deviations =  660.05074
Iteration 69: sum of abs. weighted deviations =  659.98302
Iteration 70: sum of abs. weighted deviations =  659.83989
Iteration 71: sum of abs. weighted deviations =  659.71266
Iteration 72: sum of abs. weighted deviations =  659.65419
Iteration 73: sum of abs. weighted deviations =  659.54606
Iteration 74: sum of abs. weighted deviations =  659.49445
Iteration 75: sum of abs. weighted deviations =    659.456
Iteration 76: sum of abs. weighted deviations =  659.40618
Iteration 77: sum of abs. weighted deviations =   659.3639
Iteration 78: sum of abs. weighted deviations =  659.25925
Iteration 79: sum of abs. weighted deviations =   659.1294
Iteration 80: sum of abs. weighted deviations =    659.033
Iteration 81: sum of abs. weighted deviations =  659.00518
Iteration 82: sum of abs. weighted deviations =  658.87924
Iteration 83: sum of abs. weighted deviations =  658.82519
Iteration 84: sum of abs. weighted deviations =  658.75815
Iteration 85: sum of abs. weighted deviations =  658.54864
Iteration 86: sum of abs. weighted deviations =  658.51853
Iteration 87: sum of abs. weighted deviations =   656.6053
Iteration 88: sum of abs. weighted deviations =   656.3953
Iteration 89: sum of abs. weighted deviations =  656.09423
Iteration 90: sum of abs. weighted deviations =  655.22702
Iteration 91: sum of abs. weighted deviations =  654.79748
Iteration 92: sum of abs. weighted deviations =  654.70469
Iteration 93: sum of abs. weighted deviations =  654.63577
Iteration 94: sum of abs. weighted deviations =  654.58503
note:  alternate solutions exist
Iteration 95: sum of abs. weighted deviations =  653.25341
Iteration 96: sum of abs. weighted deviations =  653.08485
Iteration 97: sum of abs. weighted deviations =  652.94687
Iteration 98: sum of abs. weighted deviations =  651.86088
Iteration 99: sum of abs. weighted deviations =  651.80087
Iteration 100: sum of abs. weighted deviations =  651.79333
Iteration 101: sum of abs. weighted deviations =  651.76598
Iteration 102: sum of abs. weighted deviations =  651.62691
Iteration 103: sum of abs. weighted deviations =  651.50393
Iteration 104: sum of abs. weighted deviations =  651.46452
Iteration 105: sum of abs. weighted deviations =  651.41717
Iteration 106: sum of abs. weighted deviations =  651.13366
Iteration 107: sum of abs. weighted deviations =  651.10184
Iteration 108: sum of abs. weighted deviations =  651.03785
note:  alternate solutions exist
Iteration 109: sum of abs. weighted deviations =  650.89948
Iteration 110: sum of abs. weighted deviations =  650.89587
Iteration 111: sum of abs. weighted deviations =  650.82822
Iteration 112: sum of abs. weighted deviations =  650.51021
Iteration 113: sum of abs. weighted deviations =  650.47455
Iteration 114: sum of abs. weighted deviations =   650.4505
Iteration 115: sum of abs. weighted deviations =  650.43571
Iteration 116: sum of abs. weighted deviations =  650.42637
Iteration 117: sum of abs. weighted deviations =  650.41623
Iteration 118: sum of abs. weighted deviations =  650.38796
Iteration 119: sum of abs. weighted deviations =  650.32667
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Iteration 120: sum of abs. weighted deviations =  650.31364
Iteration 121: sum of abs. weighted deviations =  650.31062
Iteration 122: sum of abs. weighted deviations =  650.27475
Iteration 123: sum of abs. weighted deviations =  650.24649
Iteration 124: sum of abs. weighted deviations =  650.15344
Iteration 125: sum of abs. weighted deviations =  650.12099
Iteration 126: sum of abs. weighted deviations =  650.09791
Iteration 127: sum of abs. weighted deviations =  650.07422
Iteration 128: sum of abs. weighted deviations =  650.06966
Iteration 129: sum of abs. weighted deviations =  650.06416
Iteration 130: sum of abs. weighted deviations =  650.01771
Iteration 131: sum of abs. weighted deviations =  650.01085
Iteration 132: sum of abs. weighted deviations =  649.96009
Iteration 133: sum of abs. weighted deviations =   649.9261
Iteration 134: sum of abs. weighted deviations =  649.60838
Iteration 135: sum of abs. weighted deviations =  649.54943
note:  alternate solutions exist
Iteration 136: sum of abs. weighted deviations =  649.53976
Iteration 137: sum of abs. weighted deviations =  649.47016
Iteration 138: sum of abs. weighted deviations =  649.46909
Iteration 139: sum of abs. weighted deviations =  649.46479
Iteration 140: sum of abs. weighted deviations =  649.45777
Iteration 141: sum of abs. weighted deviations =  649.39101
Iteration 142: sum of abs. weighted deviations =  649.38786
Iteration 143: sum of abs. weighted deviations =  649.38282
Iteration 144: sum of abs. weighted deviations =   649.3801
Iteration 145: sum of abs. weighted deviations =  649.37958
Iteration 146: sum of abs. weighted deviations =  649.36876
Iteration 147: sum of abs. weighted deviations =  649.35917
Iteration 148: sum of abs. weighted deviations =  649.35102
Iteration 149: sum of abs. weighted deviations =  649.34664
Iteration 150: sum of abs. weighted deviations =  649.34177
Iteration 151: sum of abs. weighted deviations =   649.3314
Iteration 152: sum of abs. weighted deviations =  649.32218
Iteration 153: sum of abs. weighted deviations =  649.29472
Iteration 154: sum of abs. weighted deviations =   649.2939
Iteration 155: sum of abs. weighted deviations =  649.28875
Iteration 156: sum of abs. weighted deviations =  649.28421
Iteration 157: sum of abs. weighted deviations =  649.28177
Iteration 158: sum of abs. weighted deviations =  648.46335
Iteration 159: sum of abs. weighted deviations =  648.45816
Iteration 160: sum of abs. weighted deviations =  648.45482
Iteration 161: sum of abs. weighted deviations =  648.45196
Iteration 162: sum of abs. weighted deviations =  648.43654
note:  alternate solutions exist
Iteration 163: sum of abs. weighted deviations =   648.4347
Iteration 164: sum of abs. weighted deviations =  648.42777
Iteration 165: sum of abs. weighted deviations =  648.41118
Iteration 166: sum of abs. weighted deviations =  648.40908
Iteration 167: sum of abs. weighted deviations =  648.40639
Iteration 168: sum of abs. weighted deviations =  648.40127
Iteration 169: sum of abs. weighted deviations =  648.40089
Iteration 170: sum of abs. weighted deviations =  648.39445
Iteration 171: sum of abs. weighted deviations =  648.39224
Iteration 172: sum of abs. weighted deviations =  648.39047
Iteration 173: sum of abs. weighted deviations =  648.38978
Iteration 174: sum of abs. weighted deviations =  648.38485
Iteration 175: sum of abs. weighted deviations =  648.38297
Iteration 176: sum of abs. weighted deviations =  648.38131
Iteration 177: sum of abs. weighted deviations =   648.3804
Iteration 178: sum of abs. weighted deviations =  648.37977
Iteration 179: sum of abs. weighted deviations =  648.37942
note:  alternate solutions exist
Iteration 180: sum of abs. weighted deviations =  648.37879
Iteration 181: sum of abs. weighted deviations =  648.37776
Iteration 182: sum of abs. weighted deviations =  648.37588
Iteration 183: sum of abs. weighted deviations =  648.37508
Iteration 184: sum of abs. weighted deviations =  648.30603
Iteration 185: sum of abs. weighted deviations =  648.30425
Iteration 186: sum of abs. weighted deviations =  648.30399
Iteration 187: sum of abs. weighted deviations =  648.29911
Iteration 188: sum of abs. weighted deviations =  648.29848
Iteration 189: sum of abs. weighted deviations =  648.29709
Iteration 190: sum of abs. weighted deviations =  648.29505
Iteration 191: sum of abs. weighted deviations =  648.29432
Iteration 192: sum of abs. weighted deviations =  648.29259
Iteration 193: sum of abs. weighted deviations =  648.29051
```

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Iteration 194: sum of abs. weighted deviations =  648.28995
Iteration 195: sum of abs. weighted deviations =  648.28979
Iteration 196: sum of abs. weighted deviations =  648.28906
Iteration 197: sum of abs. weighted deviations =  648.28357
Iteration 198: sum of abs. weighted deviations =  648.28186
Iteration 199: sum of abs. weighted deviations =  648.24003
Iteration 200: sum of abs. weighted deviations =  648.23946
Iteration 201: sum of abs. weighted deviations =  648.23616
Iteration 202: sum of abs. weighted deviations =  648.21629
Iteration 203: sum of abs. weighted deviations =  648.21564
Iteration 204: sum of abs. weighted deviations =  648.21536
Iteration 205: sum of abs. weighted deviations =  648.20973
Iteration 206: sum of abs. weighted deviations =  648.20741
Iteration 207: sum of abs. weighted deviations =  648.20739
Iteration 208: sum of abs. weighted deviations =  648.20636
Iteration 209: sum of abs. weighted deviations =  648.19243
Iteration 210: sum of abs. weighted deviations =  648.19205
Iteration 211: sum of abs. weighted deviations =  648.19124
Iteration 212: sum of abs. weighted deviations =  648.19065
Iteration 213: sum of abs. weighted deviations =  648.19042
Iteration 214: sum of abs. weighted deviations =   648.1902
Iteration 215: sum of abs. weighted deviations =  648.18987
Iteration 216: sum of abs. weighted deviations =  648.18749
Iteration 217: sum of abs. weighted deviations =  648.18746
Iteration 218: sum of abs. weighted deviations =  648.18738
Iteration 219: sum of abs. weighted deviations =  648.18729

.25 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 648.1873                    Pseudo R2     =    0.4848
```

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logq	-.2182934	.0081348	-26.83	0.000	-.2342446	-.2023421
cme2	.0001905	.0000442	4.31	0.000	.0001038	.0002772
kor	.1161709	.006838	16.99	0.000	.1027625	.1295793
fcukor	.0024129	.0005783	4.17	0.000	.0012789	.003547
nfcukor	-.0049664	.0014125	-3.52	0.000	-.0077362	-.0021966
badacsony	.4622004	.0767065	6.03	0.000	.3117892	.6126116
balaton	.5390809	.076583	7.04	0.000	.3889118	.68925
bb	.4886885	.0664842	7.35	0.000	.3583218	.6190553
bfelv	.5201898	.1056743	4.92	0.000	.3129765	.7274031
bfcs	.5319727	.0717904	7.41	0.000	.3912013	.6727442
bukk	.3817929	.1812767	2.11	0.035	.0263334	.7372524
duna	.2682254	.179546	1.49	0.135	-.0838404	.6202913
dunantuli	.4098078	.0762817	5.37	0.000	.2602295	.5593861
dtk	-.3000019	.0733663	-4.09	0.000	-.4438635	-.1561403
eger	.4885747	.0661538	7.39	0.000	.3588558	.6182935
etyekbuda	.5708505	.0807135	7.07	0.000	.4125821	.7291188
fm	.4008655	.0700544	5.72	0.000	.2634981	.5382328
hb	.2964014	.0931994	3.18	0.001	.1136498	.4791531
kali	1.105156	.1799598	6.14	0.000	.752279	1.458033
kunsag	.1647987	.0737441	2.23	0.026	.0201963	.3094012
matra	.2602072	.0693672	3.75	0.000	.1241873	.3962271
mor	.6596279	.1352365	4.88	0.000	.3944471	.9248086
nsomlo	.6885191	.0930012	7.40	0.000	.5061561	.8708821
neszmely	.4493966	.1005371	4.47	0.000	.2522568	.6465364
pannon	.5627766	.128336	4.39	0.000	.3111268	.8144264
phalma	.8239415	.1128144	7.30	0.000	.6027275	1.045155
pecs	.5252869	.090496	5.80	0.000	.3478363	.7027375
sopron	.6465765	.0808928	7.99	0.000	.4879565	.8051965
szekszard	.5228138	.062167	8.41	0.000	.4009126	.644715
tokaj	.5517993	.0652405	8.46	0.000	.4238713	.6797274
tolna	.1597636	.0992234	1.61	0.107	-.0348002	.3543274
villany	.593566	.0616905	9.62	0.000	.472599	.7145329
zala	.2671613	.1622871	1.65	0.100	-.0510622	.5853848
dulo	.4037958	.0518958	7.78	0.000	.3020351	.5055565
tier1	.3918946	.0281133	13.94	0.000	.3367682	.4470209
tier2	.3356417	.0264646	12.68	0.000	.2837482	.3875352
vbordo	-.015187	.0428403	-0.35	0.723	-.0991912	.0688172
vegyeb	-.1138545	.0394643	-2.89	0.004	-.1912387	-.0364703
vnem	-.1920349	.0675462	-2.84	0.005	-.3244839	-.0595858
ffajta	-.1007379	.0350175	-2.88	0.004	-.1694027	-.0320732
fnem	-.1730192	.0733618	-2.36	0.018	-.3168719	-.0291665
muskegyeb	-.1277521	.0516431	-2.47	0.013	-.2290174	-.0264868
csfi	-.0549394	.0546118	-1.01	0.315	-.1620259	.0521472

```
       _cons |   8.206234   .0991316    82.78   0.000      8.01185    8.400618
------------------------------------------------------------------------------

. estimates store qe25

.
. *0,5 EGYBEN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pe
> cs sopron szekszard tokaj tolna villany zala dulo tier1 tier2 vbordo vegyeb vnem
ffajta fnem muskegyeb csfi, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  835.28893

Iteration  1: sum of abs. weighted deviations =  836.05407
Iteration  2: sum of abs. weighted deviations =  835.58182
Iteration  3: sum of abs. weighted deviations =   835.1426
Iteration  4: sum of abs. weighted deviations =  834.92077
Iteration  5: sum of abs. weighted deviations =  834.64334
Iteration  6: sum of abs. weighted deviations =  834.48233
Iteration  7: sum of abs. weighted deviations =  833.94474
Iteration  8: sum of abs. weighted deviations =  833.38643
Iteration  9: sum of abs. weighted deviations =   833.2406
Iteration 10: sum of abs. weighted deviations =  833.15128
Iteration 11: sum of abs. weighted deviations =  833.10067
Iteration 12: sum of abs. weighted deviations =  832.93798
Iteration 13: sum of abs. weighted deviations =  832.91126
Iteration 14: sum of abs. weighted deviations =  832.81685
Iteration 15: sum of abs. weighted deviations =  832.79719
Iteration 16: sum of abs. weighted deviations =  832.72347
Iteration 17: sum of abs. weighted deviations =  832.68258
Iteration 18: sum of abs. weighted deviations =  832.44091
Iteration 19: sum of abs. weighted deviations =  832.43601
Iteration 20: sum of abs. weighted deviations =  832.31877
Iteration 21: sum of abs. weighted deviations =  831.90671
Iteration 22: sum of abs. weighted deviations =  831.88616
Iteration 23: sum of abs. weighted deviations =  831.79076
Iteration 24: sum of abs. weighted deviations =  831.77854
Iteration 25: sum of abs. weighted deviations =  831.75384
Iteration 26: sum of abs. weighted deviations =   831.6768
Iteration 27: sum of abs. weighted deviations =  831.62202
Iteration 28: sum of abs. weighted deviations =  831.58752
Iteration 29: sum of abs. weighted deviations =  831.55259
Iteration 30: sum of abs. weighted deviations =  831.52298
Iteration 31: sum of abs. weighted deviations =   831.2966
Iteration 32: sum of abs. weighted deviations =  831.27263
Iteration 33: sum of abs. weighted deviations =  831.25292
Iteration 34: sum of abs. weighted deviations =  831.22453
Iteration 35: sum of abs. weighted deviations =  831.19237
Iteration 36: sum of abs. weighted deviations =  831.14764
Iteration 37: sum of abs. weighted deviations =   831.1455
Iteration 38: sum of abs. weighted deviations =  831.12034
note:  alternate solutions exist
Iteration 39: sum of abs. weighted deviations =  830.95538
Iteration 40: sum of abs. weighted deviations =   830.9264
Iteration 41: sum of abs. weighted deviations =  830.83434
Iteration 42: sum of abs. weighted deviations =  830.83366
Iteration 43: sum of abs. weighted deviations =  830.82625
Iteration 44: sum of abs. weighted deviations =  830.81324
Iteration 45: sum of abs. weighted deviations =  830.80701
note:  alternate solutions exist
Iteration 46: sum of abs. weighted deviations =  830.74024
Iteration 47: sum of abs. weighted deviations =  830.73699
Iteration 48: sum of abs. weighted deviations =  830.71766
Iteration 49: sum of abs. weighted deviations =  830.66824
Iteration 50: sum of abs. weighted deviations =  830.66339
Iteration 51: sum of abs. weighted deviations =  830.65597
Iteration 52: sum of abs. weighted deviations =  830.63183
Iteration 53: sum of abs. weighted deviations =   830.6268
Iteration 54: sum of abs. weighted deviations =  830.62428
Iteration 55: sum of abs. weighted deviations =  830.62341
note:  alternate solutions exist
Iteration 56: sum of abs. weighted deviations =  830.61282
Iteration 57: sum of abs. weighted deviations =  830.60733
Iteration 58: sum of abs. weighted deviations =  830.59756
Iteration 59: sum of abs. weighted deviations =  830.59482
Iteration 60: sum of abs. weighted deviations =  830.59224
```

```
Iteration 61: sum of abs. weighted deviations =  830.58893
Iteration 62: sum of abs. weighted deviations =   830.5874
note:  alternate solutions exist
Iteration 63: sum of abs. weighted deviations =  830.56605
Iteration 64: sum of abs. weighted deviations =  830.55945
Iteration 65: sum of abs. weighted deviations =  830.55942
note:  alternate solutions exist
Iteration 66: sum of abs. weighted deviations =  830.52584
Iteration 67: sum of abs. weighted deviations =  830.52128
Iteration 68: sum of abs. weighted deviations =  830.51325
Iteration 69: sum of abs. weighted deviations =    830.512
Iteration 70: sum of abs. weighted deviations =  830.51184
Iteration 71: sum of abs. weighted deviations =  830.51072
Iteration 72: sum of abs. weighted deviations =  830.50806
Iteration 73: sum of abs. weighted deviations =    830.503
Iteration 74: sum of abs. weighted deviations =  830.49767
Iteration 75: sum of abs. weighted deviations =  830.49623
Iteration 76: sum of abs. weighted deviations =  830.49243
Iteration 77: sum of abs. weighted deviations =  830.49062
Iteration 78: sum of abs. weighted deviations =  830.48951
Iteration 79: sum of abs. weighted deviations =  830.48295
Iteration 80: sum of abs. weighted deviations =   830.4825
Iteration 81: sum of abs. weighted deviations =  830.45882
Iteration 82: sum of abs. weighted deviations =  830.45484
Iteration 83: sum of abs. weighted deviations =  830.45458
Iteration 84: sum of abs. weighted deviations =  830.45417
Iteration 85: sum of abs. weighted deviations =  830.45154
Iteration 86: sum of abs. weighted deviations =  830.44912
Iteration 87: sum of abs. weighted deviations =  830.44434
Iteration 88: sum of abs. weighted deviations =  830.44197
Iteration 89: sum of abs. weighted deviations =  830.44142
Iteration 90: sum of abs. weighted deviations =  830.44113
Iteration 91: sum of abs. weighted deviations =  830.34233
Iteration 92: sum of abs. weighted deviations =  830.34034
Iteration 93: sum of abs. weighted deviations =  830.33857
Iteration 94: sum of abs. weighted deviations =  830.33856
Iteration 95: sum of abs. weighted deviations =  830.33543
Iteration 96: sum of abs. weighted deviations =  830.33488
Iteration 97: sum of abs. weighted deviations =  830.33482
Iteration 98: sum of abs. weighted deviations =  830.33331
Iteration 99: sum of abs. weighted deviations =  830.33285
Iteration 100: sum of abs. weighted deviations =  830.33263
Iteration 101: sum of abs. weighted deviations =  830.33234
Iteration 102: sum of abs. weighted deviations =  830.33182
Iteration 103: sum of abs. weighted deviations =  830.33175
Iteration 104: sum of abs. weighted deviations =  830.33167
Iteration 105: sum of abs. weighted deviations =  830.33121
Iteration 106: sum of abs. weighted deviations =  830.33044
Iteration 107: sum of abs. weighted deviations =  830.32952
Iteration 108: sum of abs. weighted deviations =  830.32949
Iteration 109: sum of abs. weighted deviations =  830.32948

Median regression                                    Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 830.3295                     Pseudo R2     =    0.4719

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2182384   .0093457   -23.35   0.000     -.236564   -.1999128
        cme2 |   .0001971   .0000409     4.82   0.000     .0001168    .0002773
         kor |   .1195397   .0076073    15.71   0.000     .1046228    .1344566
      fcukor |   .0031641   .0006721     4.71   0.000     .0018461    .0044821
     nfcukor |   -.006692   .0017618    -3.80   0.000    -.0101466   -.0032373
   badacsony |   .2324252   .0924967     2.51   0.012     .0510515    .4137989
     balaton |   .3095864   .0910962     3.40   0.001     .1309588     .488214
          bb |   .2189983   .0804685     2.72   0.007     .0612104    .3767863
       bfelv |   .1479013   .1324214     1.12   0.264    -.1117595     .407562
        bfcs |   .3118928   .0868421     3.59   0.000      .141607    .4821786
        bukk |   .2207966   .2281699     0.97   0.333    -.2266142    .6682074
        duna |   -.154941   .2273915    -0.68   0.496    -.6008255    .2909435
   dunantuli |    .088396   .0904733     0.98   0.329      -.08901    .2658021
         dtk |  -.5493858   .0884078    -6.21   0.000    -.7227418   -.3760299
        eger |   .3002486   .0799414     3.76   0.000     .1434941    .4570031
   etyekbuda |   .3909073   .0969524     4.03   0.000     .2007965    .5810181
          fm |   .2407356   .0843833     2.85   0.004     .0752712    .4061999
          hb |   .0611324   .1128233     0.54   0.588     -.160099    .2823639
```

```
        kali |   .6713416   .2274747     2.95   0.003     .2252939    1.117389
      kunsag |  -.0435591   .0894484    -0.49   0.626    -.2189555    .1318373
       matra |  -.0062729   .0833094    -0.08   0.940    -.1696316    .1570858
         mor |   .2520004   .1645465     1.53   0.126    -.0706534    .5746542
      nsomlo |    .381281   .1121657     3.40   0.001      .161339    .6012231
    neszmely |   .1320987   .1232547     1.07   0.284    -.1095873    .3737848
      pannon |   .2874936   .1522402     1.89   0.059    -.0110292    .5860165
      phalma |   .5199053   .1367491     3.80   0.000     .2517585     .788052
        pecs |   .1821067   .1085973     1.68   0.094    -.0308382    .3950515
      sopron |   .3203147   .0984547     3.25   0.001     .1272581    .5133713
   szekszard |   .2826001    .075336     3.75   0.000     .1348762    .4303241
       tokaj |   .3033492   .0779705     3.89   0.000     .1504593    .4562391
       tolna |   .0097604   .1208938     0.08   0.936    -.2272962    .2468169
     villany |   .3746243     .07388     5.07   0.000     .2297555    .5194931
        zala |   .0091685   .2154547     0.04   0.966    -.4133096    .4316465
        dulo |   .3969872   .0611173     6.50   0.000     .2771443      .51683
       tier1 |   .3860071   .0330788    11.67   0.000     .3211439    .4508702
       tier2 |   .2921863   .0314104     9.30   0.000     .2305947    .3537779
      vbordo |   .0136029   .0479688     0.28   0.777    -.0804575    .1076634
      vegyeb |  -.1130273   .0457974    -2.47   0.014    -.2028299   -.0232246
        vnem |   -.233552   .0820648    -2.85   0.004    -.3944702   -.0726339
      ffajta |  -.0939461   .0412719    -2.28   0.023    -.1748748   -.0130173
        fnem |  -.1016205   .0887414    -1.15   0.252    -.2756305    .0723896
   muskegyeb |  -.1554417   .0609452    -2.55   0.011     -.274947   -.0359363
        csfi |  -.0969147   .0645223    -1.50   0.133    -.2234343    .0296049
       _cons |   8.661176     .11752    73.70   0.000     8.430735    8.891617
------------------------------------------------------------------------------

. estimates store qe50

.
. *0,75 EGYBEN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pe
> cs sopron szekszard tokaj tolna villany zala dulo tier1 tier2 vbordo vegyeb vnem
ffajta fnem muskegyeb csfi, quantile(75)
Iteration  1:  WLS sum of weighted deviations =   792.3542

Iteration  1: sum of abs. weighted deviations =  819.53973
Iteration  2: sum of abs. weighted deviations =  805.69645
Iteration  3: sum of abs. weighted deviations =  798.12214
Iteration  4: sum of abs. weighted deviations =  797.32433
Iteration  5: sum of abs. weighted deviations =  788.41726
Iteration  6: sum of abs. weighted deviations =   777.7367
Iteration  7: sum of abs. weighted deviations =  775.86725
Iteration  8: sum of abs. weighted deviations =  775.00408
Iteration  9: sum of abs. weighted deviations =  772.75032
Iteration 10: sum of abs. weighted deviations =  772.14312
Iteration 11: sum of abs. weighted deviations =  768.78007
Iteration 12: sum of abs. weighted deviations =  764.67862
Iteration 13: sum of abs. weighted deviations =   762.6116
Iteration 14: sum of abs. weighted deviations =  759.00608
Iteration 15: sum of abs. weighted deviations =  757.46714
Iteration 16: sum of abs. weighted deviations =   756.4635
Iteration 17: sum of abs. weighted deviations =   755.7896
Iteration 18: sum of abs. weighted deviations =  755.48308
Iteration 19: sum of abs. weighted deviations =  754.38902
Iteration 20: sum of abs. weighted deviations =  751.70592
Iteration 21: sum of abs. weighted deviations =  748.37492
Iteration 22: sum of abs. weighted deviations =  745.57158
Iteration 23: sum of abs. weighted deviations =  745.25091
Iteration 24: sum of abs. weighted deviations =  743.93511
Iteration 25: sum of abs. weighted deviations =  741.24206
Iteration 26: sum of abs. weighted deviations =  740.43583
Iteration 27: sum of abs. weighted deviations =  737.09821
Iteration 28: sum of abs. weighted deviations =  735.78979
Iteration 29: sum of abs. weighted deviations =  735.47891
Iteration 30: sum of abs. weighted deviations =  734.09794
Iteration 31: sum of abs. weighted deviations =  732.30394
Iteration 32: sum of abs. weighted deviations =   730.5409
Iteration 33: sum of abs. weighted deviations =  729.81109
Iteration 34: sum of abs. weighted deviations =  728.85715
Iteration 35: sum of abs. weighted deviations =  726.78189
Iteration 36: sum of abs. weighted deviations =  726.23304
Iteration 37: sum of abs. weighted deviations =  725.62162
Iteration 38: sum of abs. weighted deviations =  723.76589
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Iteration 39: sum of abs. weighted deviations =  722.34465
Iteration 40: sum of abs. weighted deviations =  722.31103
Iteration 41: sum of abs. weighted deviations =  721.30977
Iteration 42: sum of abs. weighted deviations =  720.76136
Iteration 43: sum of abs. weighted deviations =  719.58339
Iteration 44: sum of abs. weighted deviations =  719.26458
Iteration 45: sum of abs. weighted deviations =  718.84717
Iteration 46: sum of abs. weighted deviations =  713.93506
Iteration 47: sum of abs. weighted deviations =  713.53643
Iteration 48: sum of abs. weighted deviations =  713.39988
Iteration 49: sum of abs. weighted deviations =  713.15504
Iteration 50: sum of abs. weighted deviations =  712.47245
Iteration 51: sum of abs. weighted deviations =  712.04365
Iteration 52: sum of abs. weighted deviations =  712.02617
Iteration 53: sum of abs. weighted deviations =  711.90156
Iteration 54: sum of abs. weighted deviations =  710.95288
Iteration 55: sum of abs. weighted deviations =  710.40553
Iteration 56: sum of abs. weighted deviations =  710.15316
Iteration 57: sum of abs. weighted deviations =   709.9696
Iteration 58: sum of abs. weighted deviations =  709.50504
Iteration 59: sum of abs. weighted deviations =   709.4196
Iteration 60: sum of abs. weighted deviations =  705.73182
Iteration 61: sum of abs. weighted deviations =  703.69859
Iteration 62: sum of abs. weighted deviations =  703.63457
Iteration 63: sum of abs. weighted deviations =  702.83861
Iteration 64: sum of abs. weighted deviations =  702.58269
Iteration 65: sum of abs. weighted deviations =  702.30249
Iteration 66: sum of abs. weighted deviations =  702.02746
Iteration 67: sum of abs. weighted deviations =   701.8987
Iteration 68: sum of abs. weighted deviations =  701.69262
Iteration 69: sum of abs. weighted deviations =  701.42958
Iteration 70: sum of abs. weighted deviations =  699.92685
Iteration 71: sum of abs. weighted deviations =  699.90356
Iteration 72: sum of abs. weighted deviations =  699.49377
Iteration 73: sum of abs. weighted deviations =  699.38259
Iteration 74: sum of abs. weighted deviations =  698.32939
Iteration 75: sum of abs. weighted deviations =  697.96276
Iteration 76: sum of abs. weighted deviations =  697.17909
Iteration 77: sum of abs. weighted deviations =  696.56469
Iteration 78: sum of abs. weighted deviations =  696.40164
Iteration 79: sum of abs. weighted deviations =  696.21979
Iteration 80: sum of abs. weighted deviations =  695.91626
Iteration 81: sum of abs. weighted deviations =  695.84445
Iteration 82: sum of abs. weighted deviations =   695.6865
Iteration 83: sum of abs. weighted deviations =  695.62575
Iteration 84: sum of abs. weighted deviations =  695.61025
Iteration 85: sum of abs. weighted deviations =  695.48084
Iteration 86: sum of abs. weighted deviations =  695.28159
Iteration 87: sum of abs. weighted deviations =  695.11749
Iteration 88: sum of abs. weighted deviations =  692.99261
Iteration 89: sum of abs. weighted deviations =  692.95701
Iteration 90: sum of abs. weighted deviations =  692.57752
Iteration 91: sum of abs. weighted deviations =  692.44572
Iteration 92: sum of abs. weighted deviations =   692.4182
Iteration 93: sum of abs. weighted deviations =  691.89137
Iteration 94: sum of abs. weighted deviations =  691.86333
Iteration 95: sum of abs. weighted deviations =  691.75731
Iteration 96: sum of abs. weighted deviations =  691.58225
Iteration 97: sum of abs. weighted deviations =  691.52069
Iteration 98: sum of abs. weighted deviations =  691.44488
Iteration 99: sum of abs. weighted deviations =  691.34484
Iteration 100: sum of abs. weighted deviations =  690.95778
Iteration 101: sum of abs. weighted deviations =  690.89137
Iteration 102: sum of abs. weighted deviations =  690.88715
Iteration 103: sum of abs. weighted deviations =  690.49863
Iteration 104: sum of abs. weighted deviations =  690.46452
Iteration 105: sum of abs. weighted deviations =  690.40362
Iteration 106: sum of abs. weighted deviations =  690.37417
Iteration 107: sum of abs. weighted deviations =   690.3111
Iteration 108: sum of abs. weighted deviations =  690.03618
Iteration 109: sum of abs. weighted deviations =  689.84604
Iteration 110: sum of abs. weighted deviations =   689.7899
Iteration 111: sum of abs. weighted deviations =  689.47488
Iteration 112: sum of abs. weighted deviations =  689.43126
Iteration 113: sum of abs. weighted deviations =  689.42994
Iteration 114: sum of abs. weighted deviations =  689.37053
Iteration 115: sum of abs. weighted deviations =  689.29903
```

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Iteration 116: sum of abs. weighted deviations =   688.3631
Iteration 117: sum of abs. weighted deviations =  687.21991
Iteration 118: sum of abs. weighted deviations =  687.16584
Iteration 119: sum of abs. weighted deviations =  687.09305
Iteration 120: sum of abs. weighted deviations =  685.44029
Iteration 121: sum of abs. weighted deviations =  685.38773
Iteration 122: sum of abs. weighted deviations =  685.24143
Iteration 123: sum of abs. weighted deviations =  685.23576
Iteration 124: sum of abs. weighted deviations =   685.2132
Iteration 125: sum of abs. weighted deviations =  685.19718
Iteration 126: sum of abs. weighted deviations =  685.09948
Iteration 127: sum of abs. weighted deviations =  685.03509
Iteration 128: sum of abs. weighted deviations =   684.7584
Iteration 129: sum of abs. weighted deviations =   684.7153
Iteration 130: sum of abs. weighted deviations =  684.67593
Iteration 131: sum of abs. weighted deviations =  684.56194
Iteration 132: sum of abs. weighted deviations =  684.53456
Iteration 133: sum of abs. weighted deviations =  684.50964
Iteration 134: sum of abs. weighted deviations =  684.48987
Iteration 135: sum of abs. weighted deviations =   684.4348
Iteration 136: sum of abs. weighted deviations =  684.39387
Iteration 137: sum of abs. weighted deviations =  684.38021
Iteration 138: sum of abs. weighted deviations =  684.36891
Iteration 139: sum of abs. weighted deviations =  684.23226
Iteration 140: sum of abs. weighted deviations =  684.21663
Iteration 141: sum of abs. weighted deviations =    683.849
Iteration 142: sum of abs. weighted deviations =  683.83556
Iteration 143: sum of abs. weighted deviations =  683.80685
Iteration 144: sum of abs. weighted deviations =  683.78535
Iteration 145: sum of abs. weighted deviations =  683.76762
Iteration 146: sum of abs. weighted deviations =  682.95827
Iteration 147: sum of abs. weighted deviations =  682.68393
Iteration 148: sum of abs. weighted deviations =   682.6827
Iteration 149: sum of abs. weighted deviations =  682.11689
Iteration 150: sum of abs. weighted deviations =  681.78225
Iteration 151: sum of abs. weighted deviations =  681.18025
Iteration 152: sum of abs. weighted deviations =  681.09788
Iteration 153: sum of abs. weighted deviations =  680.97606
Iteration 154: sum of abs. weighted deviations =  680.91589
Iteration 155: sum of abs. weighted deviations =   680.7015
Iteration 156: sum of abs. weighted deviations =  680.59632
Iteration 157: sum of abs. weighted deviations =  680.56521
Iteration 158: sum of abs. weighted deviations =  680.53836
Iteration 159: sum of abs. weighted deviations =  680.46126
Iteration 160: sum of abs. weighted deviations =  680.44243
Iteration 161: sum of abs. weighted deviations =   680.4215
Iteration 162: sum of abs. weighted deviations =  680.33792
Iteration 163: sum of abs. weighted deviations =  680.04944
Iteration 164: sum of abs. weighted deviations =  679.92514
Iteration 165: sum of abs. weighted deviations =  679.76079
Iteration 166: sum of abs. weighted deviations =  679.74669
Iteration 167: sum of abs. weighted deviations =  679.72942
Iteration 168: sum of abs. weighted deviations =  679.64287
Iteration 169: sum of abs. weighted deviations =  679.64114
Iteration 170: sum of abs. weighted deviations =  679.60511
Iteration 171: sum of abs. weighted deviations =   679.5851
Iteration 172: sum of abs. weighted deviations =  679.58128
Iteration 173: sum of abs. weighted deviations =  679.56407
Iteration 174: sum of abs. weighted deviations =  679.53349
Iteration 175: sum of abs. weighted deviations =  679.52843
Iteration 176: sum of abs. weighted deviations =  679.40719
Iteration 177: sum of abs. weighted deviations =  679.38455
Iteration 178: sum of abs. weighted deviations =   679.3828
Iteration 179: sum of abs. weighted deviations =  679.38245
Iteration 180: sum of abs. weighted deviations =  679.34657
Iteration 181: sum of abs. weighted deviations =   679.3347
Iteration 182: sum of abs. weighted deviations =  679.33322
Iteration 183: sum of abs. weighted deviations =   679.3031
Iteration 184: sum of abs. weighted deviations =  679.30124
Iteration 185: sum of abs. weighted deviations =  679.27923
Iteration 186: sum of abs. weighted deviations =  679.26496
Iteration 187: sum of abs. weighted deviations =  679.26202
Iteration 188: sum of abs. weighted deviations =  679.25723
Iteration 189: sum of abs. weighted deviations =  679.20532
Iteration 190: sum of abs. weighted deviations =  679.20514
Iteration 191: sum of abs. weighted deviations =  679.16039
Iteration 192: sum of abs. weighted deviations =  679.15171
```

```
Iteration 193: sum of abs. weighted deviations =  679.13671
Iteration 194: sum of abs. weighted deviations =  679.02593
Iteration 195: sum of abs. weighted deviations =  679.01658
Iteration 196: sum of abs. weighted deviations =  679.01278
Iteration 197: sum of abs. weighted deviations =  678.99969
Iteration 198: sum of abs. weighted deviations =  678.98999
Iteration 199: sum of abs. weighted deviations =  678.96799
Iteration 200: sum of abs. weighted deviations =  678.96394
Iteration 201: sum of abs. weighted deviations =  678.96137
Iteration 202: sum of abs. weighted deviations =   678.9596
Iteration 203: sum of abs. weighted deviations =  678.94831
Iteration 204: sum of abs. weighted deviations =   678.9366
Iteration 205: sum of abs. weighted deviations =  678.92744
Iteration 206: sum of abs. weighted deviations =  678.92529
Iteration 207: sum of abs. weighted deviations =  678.84671
Iteration 208: sum of abs. weighted deviations =  678.84604
Iteration 209: sum of abs. weighted deviations =  678.84334
Iteration 210: sum of abs. weighted deviations =  678.83262
Iteration 211: sum of abs. weighted deviations =  678.82237
Iteration 212: sum of abs. weighted deviations =  678.80893
Iteration 213: sum of abs. weighted deviations =  678.80731
Iteration 214: sum of abs. weighted deviations =  678.80432
Iteration 215: sum of abs. weighted deviations =  678.80131
Iteration 216: sum of abs. weighted deviations =   678.8003
Iteration 217: sum of abs. weighted deviations =  678.79816
Iteration 218: sum of abs. weighted deviations =  678.79679
Iteration 219: sum of abs. weighted deviations =  678.79647
Iteration 220: sum of abs. weighted deviations =  678.71493
Iteration 221: sum of abs. weighted deviations =  678.18544
Iteration 222: sum of abs. weighted deviations =  678.18009
Iteration 223: sum of abs. weighted deviations =  678.17995
Iteration 224: sum of abs. weighted deviations =  678.17853
Iteration 225: sum of abs. weighted deviations =  678.17713
Iteration 226: sum of abs. weighted deviations =  678.17565
Iteration 227: sum of abs. weighted deviations =  678.17337
Iteration 228: sum of abs. weighted deviations =  678.17327
Iteration 229: sum of abs. weighted deviations =   678.1721
Iteration 230: sum of abs. weighted deviations =  678.17146
Iteration 231: sum of abs. weighted deviations =  678.17123
Iteration 232: sum of abs. weighted deviations =  678.17106

.75 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 678.1711                    Pseudo R2     =    0.5053

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2188284   .0094396   -23.18   0.000    -.2373382   -.2003186
        cme2 |   .0002342   .0000366     6.40   0.000     .0001625    .0003059
         kor |    .143244   .0072866    19.66   0.000     .1289559     .157532
      fcukor |    .002812   .0007137     3.94   0.000     .0014126    .0042115
     nfcukor |  -.0080263   .0020007    -4.01   0.000    -.0119495   -.0041032
  badacsony |   .3415526   .0987588     3.46   0.001     .1478997    .5352055
     balaton |   .2933801    .094321     3.11   0.002     .1084292    .4783311
          bb |   .1674082   .0853364     1.96   0.050      .000075    .3347415
       bfelv |   .1739753   .1379327     1.26   0.207    -.0964924    .4444431
        bfcs |   .2147444   .0924848     2.32   0.020     .0333941    .3960948
        bukk |    .039086    .220957     0.18   0.860    -.3941814    .4723534
        duna |   .0890385    .220063     0.40   0.686    -.3424758    .5205529
   dunantuli |  -.0084804   .0931581    -0.09   0.927     -.191151    .1741902
         dtk |  -.5236539   .0910852    -5.75   0.000    -.7022599    -.345048
        eger |   .2876571   .0833939     3.45   0.001     .1241326    .4511815
   etyekbuda |   .2997127   .1015012     2.95   0.003     .1006823    .4987431
          fm |   .1404158   .0886707     1.58   0.113    -.0334558    .3142873
          hb |   .0260676   .1181598     0.22   0.825     -.205628    .2577631
        kali |   .9477138   .2208444     4.29   0.000     .5146673     1.38076
      kunsag |  -.1168109   .0926581    -1.26   0.208    -.2985012    .0648793
       matra |   -.096108   .0877243    -1.10   0.273    -.2681238    .0759077
         mor |    .094472   .1674393     0.56   0.573    -.2338542    .4227982
      nsomlo |   .4243477   .1178789     3.60   0.000     .1932029    .6554926
    neszmely |   .0445694    .127749     0.35   0.727    -.2059294    .2950682
      pannon |    .241682   .1453811     1.66   0.097     -.043391     .526755
      phalma |    .476289   .1389531     3.43   0.001     .2038204    .7487577
        pecs |   .1047886   .1142906     0.92   0.359      -.11932    .3288972
      sopron |   .1523656   .1036618     1.47   0.142    -.0509013    .3556325
   szekszard |   .2198802   .0800095     2.75   0.006     .0629922    .3767682
```

```
       tokaj |   .4213563    .082768     5.09   0.000     .2590592    .5836535
       tolna |  -.0078143     .12666    -0.06   0.951    -.2561777    .2405491
     villany |   .3125293   .0780084     4.01   0.000     .1595652    .4654934
        zala |  -.2616526   .2000032    -1.31   0.191    -.6538322     .130527
        dulo |   .3178031   .0623609     5.10   0.000     .1955217    .4400845
       tier1 |    .390202   .0334749    11.66   0.000     .3245622    .4558418
       tier2 |   .2901099   .0322338     9.00   0.000     .2269038     .353316
      vbordo |   .0372134   .0466201     0.80   0.425    -.0542025    .1286292
      vegyeb |   -.091321   .0463749    -1.97   0.049     -.182256    -.000386
        vnem |  -.1671954   .0829106    -2.02   0.044     -.329772   -.0046188
      ffajta |  -.1020958   .0414498    -2.46   0.014    -.1833733   -.0208184
        fnem |  -.0909878   .0888579    -1.02   0.306    -.2652263    .0832508
   muskegyeb |  -.2118282   .0620265    -3.42   0.001    -.3334539   -.0902026
        csfi |  -.1015343    .066339    -1.53   0.126    -.2316163    .0285477
       _cons |   8.895677   .1228581    72.41   0.000     8.654769    9.136585
------------------------------------------------------------------------------

. estimates store qe75

.
. *0,9 EGYBEN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eger etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma
pe
> cs sopron szekszard tokaj tolna villany zala dulo tier1 tier2 vbordo vegyeb vnem
ffajta fnem muskegyeb csfi, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  718.82877

Iteration  1: sum of abs. weighted deviations =  728.57308
Iteration  2: sum of abs. weighted deviations =  709.35939
Iteration  3: sum of abs. weighted deviations =   707.1112
Iteration  4: sum of abs. weighted deviations =  693.40899
Iteration  5: sum of abs. weighted deviations =  685.23973
Iteration  6: sum of abs. weighted deviations =  677.32961
Iteration  7: sum of abs. weighted deviations =    672.848
Iteration  8: sum of abs. weighted deviations =  661.94977
Iteration  9: sum of abs. weighted deviations =  659.44708
Iteration 10: sum of abs. weighted deviations =  641.80599
Iteration 11: sum of abs. weighted deviations =   634.9294
Iteration 12: sum of abs. weighted deviations =  615.84505
Iteration 13: sum of abs. weighted deviations =  607.78672
Iteration 14: sum of abs. weighted deviations =  607.42583
Iteration 15: sum of abs. weighted deviations =  591.78577
Iteration 16: sum of abs. weighted deviations =  583.23241
Iteration 17: sum of abs. weighted deviations =  581.75081
Iteration 18: sum of abs. weighted deviations =  580.27272
Iteration 19: sum of abs. weighted deviations =  577.48606
Iteration 20: sum of abs. weighted deviations =  573.11866
Iteration 21: sum of abs. weighted deviations =  569.23261
Iteration 22: sum of abs. weighted deviations =  563.35988
Iteration 23: sum of abs. weighted deviations =  562.11682
Iteration 24: sum of abs. weighted deviations =  559.24805
Iteration 25: sum of abs. weighted deviations =  554.40513
Iteration 26: sum of abs. weighted deviations =  553.74271
Iteration 27: sum of abs. weighted deviations =  549.10464
Iteration 28: sum of abs. weighted deviations =  546.14698
Iteration 29: sum of abs. weighted deviations =  542.13827
Iteration 30: sum of abs. weighted deviations =  534.58611
Iteration 31: sum of abs. weighted deviations =   531.3258
Iteration 32: sum of abs. weighted deviations =  524.57565
Iteration 33: sum of abs. weighted deviations =  520.96776
Iteration 34: sum of abs. weighted deviations =  519.02017
Iteration 35: sum of abs. weighted deviations =  516.07482
Iteration 36: sum of abs. weighted deviations =  513.84416
Iteration 37: sum of abs. weighted deviations =  513.21316
Iteration 38: sum of abs. weighted deviations =  511.75862
Iteration 39: sum of abs. weighted deviations =  507.86454
Iteration 40: sum of abs. weighted deviations =  497.80212
Iteration 41: sum of abs. weighted deviations =  496.42821
Iteration 42: sum of abs. weighted deviations =  495.84453
Iteration 43: sum of abs. weighted deviations =   493.6954
Iteration 44: sum of abs. weighted deviations =  492.90507
Iteration 45: sum of abs. weighted deviations =  489.78297
Iteration 46: sum of abs. weighted deviations =  489.34713
Iteration 47: sum of abs. weighted deviations =  485.18931
Iteration 48: sum of abs. weighted deviations =  484.80577
Iteration 49: sum of abs. weighted deviations =  481.12336
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Iteration 50: sum of abs. weighted deviations =  478.28979
Iteration 51: sum of abs. weighted deviations =  477.47281
Iteration 52: sum of abs. weighted deviations =  473.86231
Iteration 53: sum of abs. weighted deviations =  473.06063
Iteration 54: sum of abs. weighted deviations =  466.31884
Iteration 55: sum of abs. weighted deviations =  464.56788
Iteration 56: sum of abs. weighted deviations =  463.18091
Iteration 57: sum of abs. weighted deviations =  462.39382
Iteration 58: sum of abs. weighted deviations =  460.34799
Iteration 59: sum of abs. weighted deviations =   460.0164
Iteration 60: sum of abs. weighted deviations =  459.57524
Iteration 61: sum of abs. weighted deviations =  458.32152
Iteration 62: sum of abs. weighted deviations =  457.05237
Iteration 63: sum of abs. weighted deviations =  456.81677
Iteration 64: sum of abs. weighted deviations =  455.03369
Iteration 65: sum of abs. weighted deviations =  453.26519
Iteration 66: sum of abs. weighted deviations =  452.67001
Iteration 67: sum of abs. weighted deviations =  446.39495
Iteration 68: sum of abs. weighted deviations =  445.44811
Iteration 69: sum of abs. weighted deviations =  444.98675
Iteration 70: sum of abs. weighted deviations =  444.56735
Iteration 71: sum of abs. weighted deviations =  443.97948
Iteration 72: sum of abs. weighted deviations =  443.59678
Iteration 73: sum of abs. weighted deviations =  442.94095
Iteration 74: sum of abs. weighted deviations =    439.885
Iteration 75: sum of abs. weighted deviations =  434.78875
Iteration 76: sum of abs. weighted deviations =  434.51073
Iteration 77: sum of abs. weighted deviations =  427.94737
Iteration 78: sum of abs. weighted deviations =  426.92235
Iteration 79: sum of abs. weighted deviations =  426.75451
Iteration 80: sum of abs. weighted deviations =  424.44908
Iteration 81: sum of abs. weighted deviations =   423.6734
Iteration 82: sum of abs. weighted deviations =  422.97979
Iteration 83: sum of abs. weighted deviations =  422.89413
Iteration 84: sum of abs. weighted deviations =  422.10465
Iteration 85: sum of abs. weighted deviations =  419.79808
Iteration 86: sum of abs. weighted deviations =  419.02443
Iteration 87: sum of abs. weighted deviations =  418.56205
Iteration 88: sum of abs. weighted deviations =  418.17131
Iteration 89: sum of abs. weighted deviations =  417.97609
Iteration 90: sum of abs. weighted deviations =  416.19957
Iteration 91: sum of abs. weighted deviations =   415.7754
Iteration 92: sum of abs. weighted deviations =  415.61831
Iteration 93: sum of abs. weighted deviations =  415.40316
Iteration 94: sum of abs. weighted deviations =  415.15837
Iteration 95: sum of abs. weighted deviations =  414.65878
Iteration 96: sum of abs. weighted deviations =  414.31301
Iteration 97: sum of abs. weighted deviations =  413.74761
Iteration 98: sum of abs. weighted deviations =   409.2615
Iteration 99: sum of abs. weighted deviations =  409.23558
Iteration 100: sum of abs. weighted deviations =  409.10666
Iteration 101: sum of abs. weighted deviations =  408.80416
Iteration 102: sum of abs. weighted deviations =   408.1537
Iteration 103: sum of abs. weighted deviations =  407.93046
Iteration 104: sum of abs. weighted deviations =   405.9881
Iteration 105: sum of abs. weighted deviations =  405.95027
Iteration 106: sum of abs. weighted deviations =  405.60853
Iteration 107: sum of abs. weighted deviations =  404.37487
Iteration 108: sum of abs. weighted deviations =  404.14897
Iteration 109: sum of abs. weighted deviations =  403.40235
note:  alternate solutions exist
Iteration 110: sum of abs. weighted deviations =  400.66892
Iteration 111: sum of abs. weighted deviations =  400.38305
Iteration 112: sum of abs. weighted deviations =  400.21103
Iteration 113: sum of abs. weighted deviations =  400.04682
Iteration 114: sum of abs. weighted deviations =  399.96607
Iteration 115: sum of abs. weighted deviations =  399.85635
Iteration 116: sum of abs. weighted deviations =  399.80251
Iteration 117: sum of abs. weighted deviations =  397.48508
Iteration 118: sum of abs. weighted deviations =  397.15964
Iteration 119: sum of abs. weighted deviations =  396.98102
Iteration 120: sum of abs. weighted deviations =   396.8301
Iteration 121: sum of abs. weighted deviations =   396.7716
Iteration 122: sum of abs. weighted deviations =  395.50157
Iteration 123: sum of abs. weighted deviations =  395.38404
Iteration 124: sum of abs. weighted deviations =    393.754
Iteration 125: sum of abs. weighted deviations =   391.4663
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Iteration 126: sum of abs. weighted deviations =  390.80162
Iteration 127: sum of abs. weighted deviations =  390.38034
Iteration 128: sum of abs. weighted deviations =  390.12545
Iteration 129: sum of abs. weighted deviations =  390.01397
Iteration 130: sum of abs. weighted deviations =  389.92932
Iteration 131: sum of abs. weighted deviations =  389.79135
Iteration 132: sum of abs. weighted deviations =  389.61499
Iteration 133: sum of abs. weighted deviations =  389.53293
Iteration 134: sum of abs. weighted deviations =  389.52701
Iteration 135: sum of abs. weighted deviations =  389.42604
Iteration 136: sum of abs. weighted deviations =  388.95913
Iteration 137: sum of abs. weighted deviations =  388.35387
Iteration 138: sum of abs. weighted deviations =  388.18423
Iteration 139: sum of abs. weighted deviations =  388.15891
Iteration 140: sum of abs. weighted deviations =  388.00102
Iteration 141: sum of abs. weighted deviations =  387.62136
Iteration 142: sum of abs. weighted deviations =   387.5279
Iteration 143: sum of abs. weighted deviations =  386.99896
Iteration 144: sum of abs. weighted deviations =  386.76332
Iteration 145: sum of abs. weighted deviations =  386.72758
Iteration 146: sum of abs. weighted deviations =  386.41997
Iteration 147: sum of abs. weighted deviations =  386.33789
Iteration 148: sum of abs. weighted deviations =  386.25344
Iteration 149: sum of abs. weighted deviations =  386.25201
Iteration 150: sum of abs. weighted deviations =  386.24284
Iteration 151: sum of abs. weighted deviations =  386.18199
Iteration 152: sum of abs. weighted deviations =  385.81834
Iteration 153: sum of abs. weighted deviations =  385.74879
Iteration 154: sum of abs. weighted deviations =  385.72427
Iteration 155: sum of abs. weighted deviations =  385.68271
Iteration 156: sum of abs. weighted deviations =  385.58251
Iteration 157: sum of abs. weighted deviations =  385.43862
Iteration 158: sum of abs. weighted deviations =  385.43242
Iteration 159: sum of abs. weighted deviations =  385.39173
Iteration 160: sum of abs. weighted deviations =  385.37782
Iteration 161: sum of abs. weighted deviations =  385.28315
Iteration 162: sum of abs. weighted deviations =  385.16963
Iteration 163: sum of abs. weighted deviations =  385.14177
Iteration 164: sum of abs. weighted deviations =  385.10559
Iteration 165: sum of abs. weighted deviations =  385.05119
Iteration 166: sum of abs. weighted deviations =  385.04963
Iteration 167: sum of abs. weighted deviations =  384.99125
Iteration 168: sum of abs. weighted deviations =  384.95275
Iteration 169: sum of abs. weighted deviations =  384.68661
Iteration 170: sum of abs. weighted deviations =  384.66943
Iteration 171: sum of abs. weighted deviations =  384.66837
Iteration 172: sum of abs. weighted deviations =  384.60068
Iteration 173: sum of abs. weighted deviations =  383.54422
Iteration 174: sum of abs. weighted deviations =  383.52348
Iteration 175: sum of abs. weighted deviations =  383.49621
Iteration 176: sum of abs. weighted deviations =  383.48689
Iteration 177: sum of abs. weighted deviations =  383.47237
Iteration 178: sum of abs. weighted deviations =  383.45529
Iteration 179: sum of abs. weighted deviations =  383.40748
Iteration 180: sum of abs. weighted deviations =  383.36764
Iteration 181: sum of abs. weighted deviations =  383.36635
Iteration 182: sum of abs. weighted deviations =  383.34475
Iteration 183: sum of abs. weighted deviations =  383.32275
Iteration 184: sum of abs. weighted deviations =  383.30687
Iteration 185: sum of abs. weighted deviations =  382.25363
Iteration 186: sum of abs. weighted deviations =  382.25138
Iteration 187: sum of abs. weighted deviations =  382.22902
Iteration 188: sum of abs. weighted deviations =  382.21864
Iteration 189: sum of abs. weighted deviations =  382.20721
Iteration 190: sum of abs. weighted deviations =  382.20179
Iteration 191: sum of abs. weighted deviations =  382.19712
Iteration 192: sum of abs. weighted deviations =    381.246
Iteration 193: sum of abs. weighted deviations =  381.24038
Iteration 194: sum of abs. weighted deviations =  381.20953
Iteration 195: sum of abs. weighted deviations =  381.13687
note:  alternate solutions exist
Iteration 196: sum of abs. weighted deviations =  381.07368
Iteration 197: sum of abs. weighted deviations =  381.06745
Iteration 198: sum of abs. weighted deviations =    381.065
Iteration 199: sum of abs. weighted deviations =  381.05043
Iteration 200: sum of abs. weighted deviations =  381.04361
Iteration 201: sum of abs. weighted deviations =  381.02865
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Iteration 202: sum of abs. weighted deviations =  381.00753
Iteration 203: sum of abs. weighted deviations =  381.00553
Iteration 204: sum of abs. weighted deviations =   381.0021
Iteration 205: sum of abs. weighted deviations =  380.99469
Iteration 206: sum of abs. weighted deviations =  380.99204
Iteration 207: sum of abs. weighted deviations =  380.98963
Iteration 208: sum of abs. weighted deviations =  380.98669
Iteration 209: sum of abs. weighted deviations =  380.97953
Iteration 210: sum of abs. weighted deviations =  380.97632
Iteration 211: sum of abs. weighted deviations =  380.97194
Iteration 212: sum of abs. weighted deviations =  380.96628
Iteration 213: sum of abs. weighted deviations =  380.54742
Iteration 214: sum of abs. weighted deviations =  379.18497
Iteration 215: sum of abs. weighted deviations =  379.04693
Iteration 216: sum of abs. weighted deviations =  378.92398
Iteration 217: sum of abs. weighted deviations =   378.8632
Iteration 218: sum of abs. weighted deviations =  378.74909
Iteration 219: sum of abs. weighted deviations =  378.71716
Iteration 220: sum of abs. weighted deviations =  378.70681
Iteration 221: sum of abs. weighted deviations =  378.68047
Iteration 222: sum of abs. weighted deviations =  378.53764
Iteration 223: sum of abs. weighted deviations =  378.47112
Iteration 224: sum of abs. weighted deviations =  378.44763
Iteration 225: sum of abs. weighted deviations =  378.44038
Iteration 226: sum of abs. weighted deviations =  378.38085
Iteration 227: sum of abs. weighted deviations =  378.32081
Iteration 228: sum of abs. weighted deviations =  378.31246
Iteration 229: sum of abs. weighted deviations =  378.29666
Iteration 230: sum of abs. weighted deviations =   378.2888
Iteration 231: sum of abs. weighted deviations =  378.28699
Iteration 232: sum of abs. weighted deviations =  378.28467
Iteration 233: sum of abs. weighted deviations =  378.27197
Iteration 234: sum of abs. weighted deviations =  378.22191
Iteration 235: sum of abs. weighted deviations =  378.20465
Iteration 236: sum of abs. weighted deviations =  378.19617
Iteration 237: sum of abs. weighted deviations =  378.19542
Iteration 238: sum of abs. weighted deviations =  378.18696
Iteration 239: sum of abs. weighted deviations =  378.17549
Iteration 240: sum of abs. weighted deviations =  378.17393
Iteration 241: sum of abs. weighted deviations =  378.16499
Iteration 242: sum of abs. weighted deviations =  378.12134
Iteration 243: sum of abs. weighted deviations =  378.07195
Iteration 244: sum of abs. weighted deviations =  378.03293
Iteration 245: sum of abs. weighted deviations =  378.01083
Iteration 246: sum of abs. weighted deviations =  377.99705
Iteration 247: sum of abs. weighted deviations =  377.98987
Iteration 248: sum of abs. weighted deviations =  377.98892
Iteration 249: sum of abs. weighted deviations =  377.81605
Iteration 250: sum of abs. weighted deviations =  377.80544
Iteration 251: sum of abs. weighted deviations =  377.80103
Iteration 252: sum of abs. weighted deviations =  377.78231
Iteration 253: sum of abs. weighted deviations =  377.77881
Iteration 254: sum of abs. weighted deviations =  377.76498
Iteration 255: sum of abs. weighted deviations =  377.73263
Iteration 256: sum of abs. weighted deviations =   377.7219
Iteration 257: sum of abs. weighted deviations =  377.71618
Iteration 258: sum of abs. weighted deviations =  377.69928
Iteration 259: sum of abs. weighted deviations =  377.69616
Iteration 260: sum of abs. weighted deviations =  377.69595
Iteration 261: sum of abs. weighted deviations =  377.69584
Iteration 262: sum of abs. weighted deviations =   377.6942
Iteration 263: sum of abs. weighted deviations =  377.69256
Iteration 264: sum of abs. weighted deviations =  377.69218
Iteration 265: sum of abs. weighted deviations =  377.63865
Iteration 266: sum of abs. weighted deviations =  377.63462
Iteration 267: sum of abs. weighted deviations =  377.62932
Iteration 268: sum of abs. weighted deviations =  377.62811
Iteration 269: sum of abs. weighted deviations =  377.56419
Iteration 270: sum of abs. weighted deviations =  377.56417
Iteration 271: sum of abs. weighted deviations =  377.56103
Iteration 272: sum of abs. weighted deviations =  377.55537
Iteration 273: sum of abs. weighted deviations =  377.55474
Iteration 274: sum of abs. weighted deviations =  377.54917
Iteration 275: sum of abs. weighted deviations =  377.54891
Iteration 276: sum of abs. weighted deviations =   377.5464
Iteration 277: sum of abs. weighted deviations =   377.5229
Iteration 278: sum of abs. weighted deviations =  377.52198
```

```
Iteration 279: sum of abs. weighted deviations =  377.51444
Iteration 280: sum of abs. weighted deviations =  377.51412
Iteration 281: sum of abs. weighted deviations =  377.51362

.9 Quantile regression                              Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 377.5136                    Pseudo R2     =    0.5499

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2025056   .0121629   -16.65   0.000    -.2263554   -.1786558
        cme2 |   .0002219   .0000433     5.13   0.000     .0001371    .0003068
         kor |   .1872293   .0090729    20.64   0.000     .1694386      .20502
      fcukor |   .0024324   .0009404     2.59   0.010     .0005884    .0042765
     nfcukor |  -.0073522   .0027316    -2.69   0.007    -.0127085    -.001996
   badacsony |   .0793642   .1168073     0.68   0.497    -.1496794    .3084078
     balaton |   .0637975   .1169933     0.55   0.586    -.1656109    .2932058
          bb |  -.0725125   .1028968    -0.70   0.481    -.2742794    .1292544
       bfelv |  -.0179078   .1629419    -0.11   0.912    -.3374153    .3015996
        bfcs |  -.0670385   .1116412    -0.60   0.548     -.285952     .151875
        bukk |   .4054129   .1332082     3.04   0.002     .1442094    .6666164
        duna |  -.2517239   .1285124    -1.96   0.050    -.5037197    .0002719
   dunantuli |  -.2183614   .1134422    -1.92   0.054    -.4408065    .0040837
         dtk |  -.5782877   .1124253    -5.14   0.000    -.7987387   -.3578367
        eger |  -.0080435   .1021639    -0.08   0.937    -.2083733    .1922863
   etyekbuda |   .0090184   .1190858     0.08   0.940    -.2244931    .2425299
          fm |  -.1846111   .1086211    -1.70   0.089    -.3976026    .0283805
          hb |  -.1491956   .1479375    -1.01   0.313    -.4392814    .1408902
        kali |   .5523069   .1302834     4.24   0.000     .2968385    .8077754
     kunsag |  -.3668967   .1149051    -3.19   0.001    -.5922103   -.1415831
       matra |  -.3259463   .1058387    -3.08   0.002    -.5334819   -.1184108
         mor |  -.2621281   .1968526    -1.33   0.183    -.6481298    .1238737
      nsomlo |   .1244767   .1464808     0.85   0.396    -.1627527    .4117061
    neszmely |  -.2691495   .1559931    -1.73   0.085    -.5750312    .0367322
     pannon |  -.0280635   .1693729    -0.17   0.868    -.3601813    .3040543
      phalma |   .0812711   .1704375     0.48   0.634    -.2529341    .4154763
        pecs |  -.0402808   .1397443    -0.29   0.773    -.3143008    .2337393
      sopron |  -.1625332   .1254969    -1.30   0.195     -.408616    .0835495
   szekszard |  -.1093599   .0962899    -1.14   0.256    -.2981716    .0794518
       tokaj |   .2611524   .1003137     2.60   0.009     .0644504    .4578543
       tolna |  -.3892555   .1570387    -2.48   0.013    -.6971876   -.0813235
     villany |  -.0034485   .0926921    -0.04   0.970    -.1852053    .1783084
        zala |    -.51014   .1251208    -4.08   0.000    -.7554852   -.2647947
        dulo |   .4231145   .0779062     5.43   0.000     .2703508    .5758781
       tier1 |    .431507   .0424283    10.17   0.000     .3483108    .5147031
       tier2 |   .2920347   .0401728     7.27   0.000     .2132611    .3708082
      vbordo |   .1589744   .0543013     2.93   0.003     .0524968    .2654519
      vegyeb |  -.0283177   .0573619    -0.49   0.622    -.1407968    .0841614
        vnem |  -.0549483   .1036832    -0.53   0.596    -.2582574    .1483607
      ffajta |  -.0578431   .0499267    -1.16   0.247    -.1557427    .0400564
        fnem |  -.1645477   .1181304    -1.39   0.164    -.3961858    .0670903
   muskegyeb |  -.1978534   .0762869    -2.59   0.010    -.3474419    -.048265
        csfi |  -.1018619   .0833327    -1.22   0.222    -.2652662    .0615425
       _cons |    9.09258   .1500942    60.58   0.000     8.798265    9.386895
------------------------------------------------------------------------------

. estimates store qe90
```

5. Models B1.1-7

```
. *Kkorl
. reg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs ens10e
etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron sz
> ekszard tbk tnbk tolna vclass vprem zala, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 33,  2638) =   56.19
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4391
                                                       Root MSE      =  .60578

------------------------------------------------------------------------------
```

```
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .8540602   .1236316     6.91   0.000     .6116355    1.096485
     balaton |   .3526544   .1212412     2.91   0.004     .1149168    .5903919
          bb |    .572901   .1138521     5.03   0.000     .3496526    .7961494
       bfelv |   .5539258   .1177445     4.70   0.000     .3230449    .7848067
        bfcs |    .707812    .112825     6.27   0.000     .4865775    .9290465
        bukk |    .674426   .2126319     3.17   0.002     .2574838    1.091368
        duna |   .4598806   .2056878     2.24   0.025     .0565548    .8632064
   dunantuli |   .0775705   .1264816     0.61   0.540    -.1704427    .3255836
         dtk |  -.7892762   .1171478    -6.74   0.000    -1.018987   -.5595654
      eclass |   .4400567    .116754     3.77   0.000      .211118    .6689954
        esup |   1.470857   .1587307     9.27   0.000     1.159608    1.782106
         egs |   1.876775   .2712323     6.92   0.000     1.344925    2.408624
      ens10e |   1.469178   .1634193     8.99   0.000     1.148735    1.789621
   etyekbuda |   .5055251   .1215435     4.16   0.000      .267195    .7438553
          fm |   .4133921   .1226905     3.37   0.001     .1728128    .6539714
          hb |   .2745229   .1237798     2.22   0.027     .0318075    .5172382
        kali |   1.275819   .2291148     5.57   0.000     .8265565    1.725082
     kunsag |   .2976394   .1123253     2.65   0.008     .0773849    .5178939
       matra |   .2229573   .1136861     1.96   0.050     .0000343    .4458802
         mor |   .4745102   .1185389     4.00   0.000     .2420716    .7069488
      nsomlo |   .8569149   .1314554     6.52   0.000     .5991488    1.114681
    neszmely |   .5127785   .1271146     4.03   0.000     .2635241    .7620329
      pannon |   .3223611   .1162102     2.77   0.006     .0944888    .5502333
      phalma |     .73695   .1310351     5.62   0.000     .4800081     .993892
        pecs |   .5769329   .1210837     4.76   0.000     .3395043    .8143615
      sopron |   .9229731   .1210523     7.62   0.000      .685606     1.16034
   szekszard |   .7760449   .1086854     7.14   0.000     .5629277    .9891621
         tbk |   2.264637   .1480443    15.30   0.000     1.974342    2.554932
        tnbk |   .9691877   .1148457     8.44   0.000     .7439909    1.194384
      tolna |   .3603183   .1485381     2.43   0.015     .0690555    .6515812
      vclass |   .5704623   .1072722     5.32   0.000     .3601162    .7808085
       vprem |   1.692223   .1180986    14.33   0.000     1.460648    1.923799
        zala |   .5609949   .1452478     3.86   0.000     .2761837     .845806
       _cons |    6.83114   .1037641    65.83   0.000     6.627673    7.034607
------------------------------------------------------------------------------

. estimates store Kkorl

.
. *Kkozt1 +dulo
. reg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs ens10e
etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron sz
> ekszard tbk tnbk tolna vclass vprem zala dulo, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 34,  2637) =   59.41
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4640
                                                       Root MSE      =  .59226

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .8540602    .123655     6.91   0.000     .6115895    1.096531
     balaton |   .3526544   .1212642     2.91   0.004     .1148717     .590437
          bb |   .5240831   .1131371     4.63   0.000     .3022366    .7459296
       bfelv |   .5539258   .1177668     4.70   0.000     .3230011    .7848505
        bfcs |   .6573247   .1121283     5.86   0.000     .4374563    .8771931
        bukk |    .674426   .2126722     3.17   0.002     .2574047    1.091447
        duna |   .4598806   .2057268     2.24   0.025     .0564783    .8632829
   dunantuli |   .0775705   .1265056     0.61   0.540    -.1704898    .3256307
         dtk |  -.7892762     .11717    -6.74   0.000    -1.019031   -.5595218
      eclass |   .4298658   .1168613     3.68   0.000     .2007167    .6590149
        esup |   1.241561   .1562563     7.95   0.000     .9351634    1.547958
         egs |   1.581965   .2601214     6.08   0.000     1.071902    2.092028
      ens10e |   1.278098   .1699394     7.52   0.000     .9448697    1.611326
   etyekbuda |   .4951025   .1211385     4.09   0.000     .2575665    .7326386
          fm |   .4013239   .1224168     3.28   0.001     .1612811    .6413667
          hb |   .2745229   .1238033     2.22   0.027     .0317615    .5172842
        kali |   1.275819   .2291583     5.57   0.000     .8264712    1.725168
      kunsag |   .2903215   .1125293     2.58   0.010     .0696668    .5109762
       matra |   .2229573   .1137077     1.96   0.050    -8.02e-06    .4459225
         mor |   .4745102   .1185614     4.00   0.000     .2420275    .7069929
```

```
     nsomlo |   .8569149   .1314803     6.52   0.000     .5990999     1.11473
   neszmely |   .4502431    .120081     3.75   0.000     .2147806    .6857056
     pannon |   .3223611   .1162322     2.77   0.006     .0944455    .5502766
     phalma |     .73695     .13106     5.62   0.000     .4799593    .9939408
       pecs |   .5769329   .1211067     4.76   0.000     .3394592    .8144066
     sopron |   .9024391   .1194053     7.56   0.000     .6683016    1.136577
  szekszard |   .7496722   .1084132     6.91   0.000     .5370887    .9622556
        tbk |   2.249844   .1469166    15.31   0.000      1.96176    2.537927
       tnbk |   .8818367   .1137877     7.75   0.000     .6587144    1.104959
      tolna |   .3603183   .1485662     2.43   0.015     .0690002    .6516365
     vclass |   .5679879   .1072246     5.30   0.000     .3577351    .7782407
      vprem |   1.615011   .1192931    13.54   0.000     1.381094    1.848929
       zala |   .5609949   .1452753     3.86   0.000     .2761297      .84586
       dulo |   .6878894   .0566522    12.14   0.000      .576802    .7989767
      _cons |    6.83114   .1037838    65.82   0.000     6.627634    7.034646
------------------------------------------------------------------------------

. estimates store Kkozt1

.
. *Kkozt2 +egyéni márkák
. reg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs ens10e
etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron sz
> ekszard tbk tnbk tolna vclass vprem zala dulo tier1 tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 36,  2635) =   66.00
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4996
                                                       Root MSE      =   .5725

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .7487708   .1192866     6.28   0.000     .5148659    .9826758
     balaton |   .3429465   .1143266     3.00   0.003     .1187675    .5671254
          bb |   .4742848   .1067451     4.44   0.000     .2649722    .6835974
       bfelv |    .567892   .1130936     5.02   0.000     .3461308    .7896533
        bfcs |    .570194   .1088359     5.24   0.000     .3567814    .7836065
        bukk |   .7277248     .20962     3.47   0.001     .3166883    1.138761
        duna |   .5131793   .2025645     2.53   0.011     .1159777     .910381
   dunantuli |   .0317542   .1176966     0.27   0.787    -.1990329    .2625413
         dtk |  -.7493813   .1102021    -6.80   0.000    -.9654727   -.5332898
      eclass |   .3730047   .1095085     3.41   0.001     .1582734    .5877361
        esup |   1.193984   .1479355     8.07   0.000     .9039026    1.484066
         egs |    1.33554   .2617875     5.10   0.000     .8222103     1.84887
      ens10e |     1.2242   .1554365     7.88   0.000     .9194103     1.52899
   etyekbuda |   .4606526   .1157439     3.98   0.000     .2336946    .6876106
          fm |   .3458013    .116008     2.98   0.003     .1183253    .5732773
          hb |   .3278216   .1183876     2.77   0.006     .0956796    .5599637
        kali |   1.329118   .2263407     5.87   0.000     .8852947    1.772942
      kunsag |    .251431   .1071639     2.35   0.019      .041297    .4615649
       matra |   .1968776   .1059744     1.86   0.063    -.0109239    .4046791
         mor |    .502092   .1077873     4.66   0.000     .2907358    .7134482
      nsomlo |   .8290999   .1215087     6.82   0.000     .5908378    1.067362
    neszmely |   .2256954    .117951     1.91   0.056    -.0055907    .4569814
      pannon |   .3023333   .1071785     2.82   0.005     .0921707    .5124958
      phalma |   .5867491   .1234575     4.75   0.000     .3446656    .8288326
        pecs |   .6233064    .115731     5.39   0.000     .3963735    .8502393
      sopron |   .7855724   .1098484     7.15   0.000     .5701745     1.00097
   szekszard |   .6645703   .1022212     6.50   0.000     .4641284    .8650121
         tbk |   2.147333   .1407679    15.25   0.000     1.871306    2.423359
        tnbk |   .8112225   .1081775     7.50   0.000      .599101    1.023344
       tolna |   .4038784   .1436433     2.81   0.005     .1222133    .6855435
      vclass |   .4581335   .1010384     4.53   0.000     .2600108    .6562562
       vprem |   1.454742   .1119565    12.99   0.000      1.23521    1.674273
        zala |   .2680843    .147136     1.82   0.069    -.0204296    .5565981
        dulo |   .6278229   .0546105    11.50   0.000     .5207391    .7349068
       tier1 |   .3116378   .0330245     9.44   0.000     .2468813    .3763944
       tier2 |    .360038   .0301859    11.93   0.000     .3008475    .4192285
       _cons |   6.777841   .0972419    69.70   0.000     6.587163     6.96852
------------------------------------------------------------------------------

. estimates store Kkozt2

.
```

```
. *Kkozt3 +beltartalom
. reg logp cme2 fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna dunantul dtk
eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon p
> halma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1 tier2,
vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 39,  2632) =   71.42
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5791
                                                       Root MSE      =  .52538

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        cme2 |   .0003444    .000092     3.74   0.000      .000164    .0005249
      fcukor |   .0026907   .0008497     3.17   0.002     .0010246    .0043569
     nfcukor |  -.0149419   .0017142    -8.72   0.000    -.0183032   -.0115805
   badacsony |   .6058545   .1136408     5.33   0.000     .3830201    .8286889
     balaton |   .3068195   .1050756     2.92   0.004     .1007804    .5128586
          bb |   .3456242   .0985542     3.51   0.000     .1523727    .5388757
       bfelv |   .4194563   .1068651     3.93   0.000     .2099082    .6290044
        bfcs |   .4542234   .1016503     4.47   0.000     .2549009    .6535459
        bukk |   .6433684   .1999938     3.22   0.001     .2512074    1.035529
        duna |   .3507211   .1858382     1.89   0.059    -.0136827    .7151248
   dunantuli |   .0038213   .1079726     0.04   0.972    -.2078986    .2155411
         dtk |  -.7938687   .1048113    -7.57   0.000    -.9993896   -.5883478
      eclass |   .2310791   .1039406     2.22   0.026     .0272656    .4348926
        esup |   .9701764   .1488485     6.52   0.000     .6783044    1.262048
         egs |    1.15357   .2708831     4.26   0.000      .622405    1.684736
      ens10e |     1.0732   .1500982     7.15   0.000     .7788775    1.367522
   etyekbuda |   .3637071    .109582     3.32   0.001     .1488315    .5785827
          fm |   .3009953   .1060182     2.84   0.005     .0931078    .5088828
          hb |   .1421295   .1108019     1.28   0.200    -.0751382    .3593972
        kali |   1.108085   .1929746     5.74   0.000     .7296877    1.486482
      kunsag |    .115006   .0983428     1.17   0.242    -.0778311     .307843
       matra |   .0905843   .0985232     0.92   0.358    -.1026064    .2837751
         mor |   .4074149   .1031465     3.95   0.000     .2051584    .6096714
      nsomlo |   .6783708   .1175502     5.77   0.000     .4478706    .9088709
    neszmely |   .1381651   .1109312     1.25   0.213    -.0793561    .3556864
      pannon |   .2076429   .1009584     2.06   0.040     .0096771    .4056087
      phalma |   .5099541   .1156116     4.41   0.000     .2832553     .736653
        pecs |   .4601121   .1042842     4.41   0.000     .2556247    .6645994
      sopron |    .667816   .1025502     6.51   0.000     .4667289    .8689031
   szekszard |   .5026599   .0969869     5.18   0.000     .3124816    .6928382
         tbk |   .9957098   .1547162     6.44   0.000     .6923322    1.299087
        tnbk |   .5173111   .1014916     5.10   0.000     .3182997    .7163225
       tolna |   .2754141   .1320312     2.09   0.037     .0165187    .5343095
      vclass |   .3207384   .0951136     3.37   0.001     .1342335    .5072433
       vprem |    1.21709   .1121504    10.85   0.000     .9971786    1.437002
        zala |   .1650138   .1356412     1.22   0.224    -.1009603     .430988
        dulo |    .671318    .056798    11.82   0.000     .5599447    .7826913
       tier1 |   .2840716   .0297716     9.54   0.000     .2256934    .3424497
       tier2 |   .3162413   .0276012    11.46   0.000      .262119    .3703636
       _cons |   6.722281   .1026457    65.49   0.000     6.521007    6.923556
------------------------------------------------------------------------------

. estimates store Kkozt3

.
. *Kkozt4 +kor
. reg logp cme2 fcukor nfcukor kor badacsony balaton bb bfelv bfcs bukk duna dunantul
dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pann
> on phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1 tier2,
vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 40,  2631) =   91.92
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6431
                                                       Root MSE      =  .48387

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
        cme2 |   .0001918   .0000508     3.77   0.000     .0000921    .0002915
      fcukor |   .0027535   .0006624     4.16   0.000     .0014546    .0040525
     nfcukor |  -.0130831   .0015236    -8.59   0.000    -.0160707   -.0100955
         kor |     .13796   .0080903    17.05   0.000     .1220961     .153824
   badacsony |   .5490253   .1045432     5.25   0.000     .3440302    .7540205
     balaton |   .3596469   .0973814     3.69   0.000      .168695    .5505988
          bb |   .3502709   .0873375     4.01   0.000     .1790137    .5215281
      bfelv |   .5479758   .0996903     5.50   0.000     .3524966    .7434551
        bfcs |   .5118675   .0900284     5.69   0.000     .3353339    .6884011
        bukk |   .7211564   .1858566     3.88   0.000     .3567165    1.085596
        duna |   .3774056   .1483226     2.54   0.011     .0865648    .6682464
   dunantuli |   .1096946    .098989     1.11   0.268    -.0844096    .3037988
         dtk |  -.6648107   .0959318    -6.93   0.000    -.8529201   -.4767013
      eclass |   .1897778   .0926675     2.05   0.041     .0080692    .3714863
        esup |   .7560695   .1330106     5.68   0.000     .4952536    1.016885
         egs |   1.063041   .2655281     4.00   0.000     .5423758    1.583706
      ens10e |   .3433818   .1422767     2.41   0.016     .0643963    .6223673
   etyekbuda |   .4094463   .0970552     4.22   0.000      .219134    .5997586
          fm |   .3296681   .0935674     3.52   0.000      .146195    .5131412
          hb |   .1472349   .1011721     1.46   0.146    -.0511501    .3456199
        kali |   1.083035   .1539759     7.03   0.000      .781109    1.384961
      kunsag |   .1540838   .0889233     1.73   0.083    -.0202829    .3284504
       matra |   .1309318   .0884594     1.48   0.139    -.0425253    .3043889
         mor |   .5298504   .0965229     5.49   0.000     .3405818    .7191189
      nsomlo |   .6471373    .115038     5.63   0.000     .4215632    .8727113
    neszmely |    .234425   .1018451     2.30   0.021     .0347203    .4341296
      pannon |   .3213816   .0981781     3.27   0.001     .1288676    .5138957
      phalma |    .675489   .1089367     6.20   0.000     .4618787    .8890993
        pecs |   .4813446   .0897805     5.36   0.000      .305297    .6573922
      sopron |   .6766958    .089812     7.53   0.000     .5005865     .852805
   szekszard |   .4649442   .0849927     5.47   0.000     .2982849    .6316034
         tbk |   .6886622   .1213113     5.68   0.000     .4507869    .9265374
        tnbk |   .4670319   .0920035     5.08   0.000     .2866253    .6474385
       tolna |   .2146879   .1116922     1.92   0.055    -.0043255    .4337014
      vclass |   .3547941   .0845603     4.20   0.000     .1889826    .5206056
       vprem |   .9693829   .0973844     9.95   0.000     .7784251    1.160341
        zala |    .205086   .1026764     2.00   0.046     .0037513    .4064206
        dulo |   .5780785   .0559173    10.34   0.000     .4684322    .6877248
       tier1 |      .2661   .0269778     9.86   0.000     .2132002    .3189998
       tier2 |   .2848816   .0257189    11.08   0.000     .2344503    .3353129
       _cons |   6.500676   .0852991    76.21   0.000     6.333416    6.667936
------------------------------------------------------------------------------

. estimates store Kkozt4

.
. *Kkozt5 +mennyiseg
. reg logp logq cme2 fcukor nfcukor kor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo
neszmely
>  pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 41,  2630) =  167.37
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7537
                                                       Root MSE      =    .402

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2235588   .0066648   -33.54   0.000    -.2366274   -.2104901
        cme2 |   .0001434   .0000446     3.22   0.001      .000056    .0002308
      fcukor |   .0024373   .0005684     4.29   0.000     .0013227    .0035519
     nfcukor |  -.0059831   .0011557    -5.18   0.000    -.0082492    -.003717
         kor |   .1212702   .0069443    17.46   0.000     .1076534     .134887
   badacsony |   .3139014   .0777941     4.04   0.000     .1613575    .4664452
     balaton |   .3461908   .0696566     4.97   0.000     .2096036    .4827781
          bb |   .2869167   .0677226     4.24   0.000     .1541216    .4197118
       bfelv |   .2616086   .0802457     3.26   0.001     .1042575    .4189596
        bfcs |    .306733    .067586     4.54   0.000     .1742059    .4392601
        bukk |   .2188201   .1728676     1.27   0.206    -.1201501    .5577903
        duna |   .1201026   .1604911     0.75   0.454     -.194599    .4348042
   dunantuli |   .1732519   .0714239     2.43   0.015     .0331991    .3133047
         dtk |  -.4621457   .0701535    -6.59   0.000    -.5997073   -.3245841
```

```
      eclass |   .2901167   .0694129     4.18   0.000     .1540073    .4262261
        esup |   .6719757   .1090721     6.16   0.000     .4580998    .8858516
         egs |   .6730825    .222905     3.02   0.003     .2359956    1.110169
      ens10e |   .2396738   .1271403     1.89   0.060    -.0096314     .488979
   etyekbuda |   .3554822   .0710772     5.00   0.000     .2161093    .4948551
          fm |   .2051876   .0690084     2.97   0.003     .0698714    .3405038
          hb |   .1314001   .0900862     1.46   0.145    -.0452468     .308047
        kali |   .8412386   .1720221     4.89   0.000     .5039263    1.178551
      kunsag |  -.0293988   .0699554    -0.42   0.674     -.166572    .1077744
       matra |   .0151025   .0639563     0.24   0.813    -.1103073    .1405122
         mor |   .2550743   .0711705     3.58   0.000     .1155185    .3946301
      nsomlo |   .3838031    .088019     4.36   0.000     .2112095    .5563967
    neszmely |    .183452   .0795753     2.31   0.021     .0274155    .3394885
      pannon |   .3194964   .0928395     3.44   0.001     .1374505    .5015423
      phalma |   .5399864   .0928347     5.82   0.000       .35795    .7220228
        pecs |   .2507731   .0760175     3.30   0.001     .1017129    .3998334
      sopron |   .3623344   .0688489     5.26   0.000     .2273309    .4973379
   szekszard |   .3488359   .0632716     5.51   0.000     .2247688    .4729031
         tbk |   .6634211   .0999093     6.64   0.000     .4675124    .8593298
        tnbk |   .3438906   .0693318     4.96   0.000     .2079401     .479841
       tolna |   .0643732   .0948434     0.68   0.497    -.1216021    .2503485
      vclass |   .3252001   .0627213     5.18   0.000      .202212    .4481881
       vprem |   .8359155   .0773289    10.81   0.000     .6842838    .9875472
        zala |  -.0128102   .0781334    -0.16   0.870    -.1660194     .140399
        dulo |   .3776458   .0483713     7.81   0.000     .2827961    .4724954
       tier1 |   .3897614   .0241134    16.16   0.000     .3424782    .4370446
       tier2 |   .2934684    .021683    13.53   0.000     .2509509    .3359859
       _cons |   8.637978   .0911652    94.75   0.000     8.459216    8.816741
------------------------------------------------------------------------------

. estimates store Kkozt5

.
. *Kkit qreg spec, vagyis: cme2, fcukor, nfcukor (+mennyiség)
. *szolofajtak
. reg logp logq cme2 fcukor nfcukor kor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo
neszmely
>  pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2 vbordo vegyeb vnem ffajta fnem muskegyeb csfi, vce(robust)

Linear regression                                      Number of obs =    2672
                                                       F( 48,  2623) =  152.37
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7588
                                                       Root MSE      =  .39836

------------------------------------------------------------------------------
             |               Robust
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2254822   .0067106   -33.60   0.000    -.2386407   -.2123236
        cme2 |   .0000971   .0000429     2.26   0.024      .000013    .0001812
      fcukor |   .0032317   .0006211     5.20   0.000     .0020138    .0044496
     nfcukor |  -.0070627   .0012973    -5.44   0.000    -.0096064   -.0045189
         kor |   .1165545   .0069381    16.80   0.000     .1029498    .1301593
   badacsony |   .3327809   .0791084     4.21   0.000     .1776598     .487902
     balaton |   .3249706   .0717372     4.53   0.000     .1843034    .4656379
          bb |   .2555427   .0677088     3.77   0.000     .1227747    .3883108
       bfelv |   .2704631   .0808072     3.35   0.001     .1120107    .4289155
        bfcs |   .2932086    .068433     4.28   0.000     .1590204    .4273967
        bukk |   .2110995    .179861     1.17   0.241    -.1415844    .5637834
        duna |   .0983079    .165445     0.59   0.552    -.2261081     .422724
   dunantuli |   .1420188   .0719683     1.97   0.049     .0008984    .2831393
         dtk |   -.463557   .0712347    -6.51   0.000     -.603239    -.323875
      eclass |   .2820441   .0708555     3.98   0.000     .1431058    .4209823
        esup |   .6767807   .1123614     6.02   0.000     .4564548    .8971067
         egs |   .6868521   .2238186     3.07   0.002     .2479732    1.125731
      ens10e |   .2376284   .1251405     1.90   0.058    -.0077557    .4830125
   etyekbuda |   .3509395   .0729654     4.81   0.000     .2078639    .4940151
          fm |   .1866549   .0702875     2.66   0.008     .0488303    .3244794
          hb |   .0888425    .090068     0.99   0.324     -.087769    .2654539
        kali |   .8079784   .1617839     4.99   0.000     .4907414    1.125215
      kunsag |  -.0487894   .0703748    -0.69   0.488    -.1867851    .0892064
       matra |  -.0024499   .0648956    -0.04   0.970    -.1297017    .1248019
         mor |   .2614339   .0710479     3.68   0.000     .1221182    .4007496
      nsomlo |   .4144084   .0894953     4.63   0.000     .2389198    .5898969
```

```
    neszmely |   .1866514    .080367     2.32   0.020     .0290622    .3442407
      pannon |   .2719268   .0950568     2.86   0.004     .0855328    .4583207
      phalma |   .5231501   .0938971     5.57   0.000     .3390302      .70727
        pecs |   .2384634   .0773779     3.08   0.002     .0867356    .3901912
      sopron |   .3277711   .0707044     4.64   0.000     .1891291    .4664132
   szekszard |   .2984409    .064636     4.62   0.000     .1716981    .4251836
         tbk |   .6832794   .0998382     6.84   0.000     .4875097    .8790491
        tnbk |   .3597061   .0703327     5.11   0.000     .2217929    .4976192
       tolna |   .0322346   .0964871     0.33   0.738    -.1569639    .2214332
      vclass |   .2807457   .0640264     4.38   0.000     .1551982    .4062931
       vprem |   .7709465   .0770472    10.01   0.000      .619867     .922026
        zala |  -.0177511   .0743354    -0.24   0.811    -.1635131    .1280108
        dulo |    .384946   .0475474     8.10   0.000     .2917117    .4781802
       tier1 |   .3954532   .0236156    16.75   0.000     .3491461    .4417603
       tier2 |   .2943299   .0217672    13.52   0.000     .2516474    .3370125
      vbordo |   .0635883    .032321     1.97   0.049     .0002111    .1269654
      vegyeb |  -.0782434   .0300562    -2.60   0.009    -.1371796   -.0193072
        vnem |  -.1127995   .0645772    -1.75   0.081    -.2394268    .0138278
      ffajta |  -.1105596   .0235803    -4.69   0.000    -.1567976   -.0643217
        fnem |  -.1138246   .0686999    -1.66   0.098    -.2485361    .0208868
   muskegyeb |  -.1447952   .0380939    -3.80   0.000    -.2194923   -.0700981
        csfi |  -.0924867    .038214    -2.42   0.016    -.1674193    -.017554
       _cons |   8.770863   .0933934    93.91   0.000     8.587731    8.953996
------------------------------------------------------------------------------

. estimates store Kkit
```

6. Restricted models B2-B6

```
. *0,1 KÜLÖN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs
ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron
szekszard tbk tnbk tolna vclass vprem zala, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  993.13047

Iteration  1: sum of abs. weighted deviations =  1040.3934
Iteration  2: sum of abs. weighted deviations =  976.71002
Iteration  3: sum of abs. weighted deviations =  910.27856
Iteration  4: sum of abs. weighted deviations =   878.8345
Iteration  5: sum of abs. weighted deviations =  856.38236
Iteration  6: sum of abs. weighted deviations =  830.47468
Iteration  7: sum of abs. weighted deviations =  815.03629
Iteration  8: sum of abs. weighted deviations =  785.94018
Iteration  9: sum of abs. weighted deviations =  771.59358
Iteration 10: sum of abs. weighted deviations =  726.71511
Iteration 11: sum of abs. weighted deviations =  693.04787
Iteration 12: sum of abs. weighted deviations =  668.83493
Iteration 13: sum of abs. weighted deviations =  655.66526
Iteration 14: sum of abs. weighted deviations =  627.88335
Iteration 15: sum of abs. weighted deviations =  608.73723
Iteration 16: sum of abs. weighted deviations =  596.49189
Iteration 17: sum of abs. weighted deviations =  563.56138
Iteration 18: sum of abs. weighted deviations =  546.85071
Iteration 19: sum of abs. weighted deviations =  538.69234
Iteration 20: sum of abs. weighted deviations =   530.7774
note:  alternate solutions exist
Iteration 21: sum of abs. weighted deviations =  526.71285
Iteration 22: sum of abs. weighted deviations =  523.55971
Iteration 23: sum of abs. weighted deviations =  518.16556
Iteration 24: sum of abs. weighted deviations =    511.427
Iteration 25: sum of abs. weighted deviations =  505.88884
Iteration 26: sum of abs. weighted deviations =  503.47129
Iteration 27: sum of abs. weighted deviations =  502.54932
Iteration 28: sum of abs. weighted deviations =  499.16614
Iteration 29: sum of abs. weighted deviations =  496.76912
Iteration 30: sum of abs. weighted deviations =   495.1956
Iteration 31: sum of abs. weighted deviations =  494.93128
Iteration 32: sum of abs. weighted deviations =  494.23349
Iteration 33: sum of abs. weighted deviations =  493.76039
Iteration 34: sum of abs. weighted deviations =  493.11065
Iteration 35: sum of abs. weighted deviations =  492.93403

.1 Quantile regression                              Number of obs =      2672
```

```
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations  492.934                     Pseudo R2     =    0.3261
```

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
badacsony	1.388799	.0192876	72.00	0.000	1.350979	1.42662
balaton	.7749891	.0191265	40.52	0.000	.7374847	.8124935
bb	1.043615	.0159366	65.49	0.000	1.012366	1.074865
bfelv	1.202299	.0225242	53.38	0.000	1.158132	1.246466
bfcs	1.207061	.0177197	68.12	0.000	1.172315	1.241807
bukk	.9829173	.0212878	46.17	0.000	.9411749	1.02466
duna	1.207312	.0197807	61.03	0.000	1.168524	1.246099
dunantuli	.6003423	.018727	32.06	0.000	.5636211	.6370635
dtk	-.2860112	.0170303	-16.79	0.000	-.3194053	-.2526171
eclass	.694818	.016948	41.00	0.000	.6615853	.7280507
esup	1.972779	.0291159	67.76	0.000	1.915687	2.029872
egs	2.299235	.0204093	112.66	0.000	2.259215	2.339255
ens10e	1.864831	.0284741	65.49	0.000	1.808998	1.920665
etyekbuda	1.043615	.0205543	50.77	0.000	1.003311	1.083919
fm	.5705447	.0177187	32.20	0.000	.5358008	.6052887
hb	1.100839	.0253702	43.39	0.000	1.051092	1.150587
kali	1.645566	.0212878	77.30	0.000	1.603824	1.687309
kunsag	.9829173	.0186739	52.64	0.000	.9463003	1.019534
matra	.696486	.0171385	40.64	0.000	.6628797	.7300923
mor	1.381265	.0167368	82.53	0.000	1.348446	1.414083
nsomlo	1.100839	.0198762	55.38	0.000	1.061865	1.139814
neszmely	1.288891	.0264619	48.71	0.000	1.237003	1.340779
pannon	1.187109	.0297296	39.93	0.000	1.128813	1.245405
phalma	1.469676	.0301011	48.82	0.000	1.410652	1.5287
pecs	1.207312	.0233285	51.75	0.000	1.161568	1.253056
sopron	1.543784	.0203645	75.81	0.000	1.503852	1.583716
szekszard	1.206311	.0141957	84.98	0.000	1.178475	1.234147
tbk	2.082155	.0182144	114.31	0.000	2.046439	2.117871
tnbk	1.206311	.0145331	83.00	0.000	1.177814	1.234809
tolna	.6319475	.027081	23.34	0.000	.5788454	.6850497
vclass	1.100839	.014466	76.10	0.000	1.072473	1.129205
vprem	2.143405	.0182551	117.41	0.000	2.107609	2.179201
zala	1.206311	.0204093	59.11	0.000	1.166291	1.246331
_cons	5.700444	.0119876	475.53	0.000	5.676938	5.72395

```
. estimates store qk10

.
. *0,25 KÜLÖN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs
ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron
szekszard tbk tnbk tolna vclass vprem zala, quantile(25)
Iteration  1:  WLS sum of weighted deviations =   1126.302

Iteration  1: sum of abs. weighted deviations =  1138.9233
Iteration  2: sum of abs. weighted deviations =  1113.7941
Iteration  3: sum of abs. weighted deviations =   1104.421
Iteration  4: sum of abs. weighted deviations =  1079.8844
Iteration  5: sum of abs. weighted deviations =  1071.0705
Iteration  6: sum of abs. weighted deviations =  1062.4775
Iteration  7: sum of abs. weighted deviations =  1043.9048
Iteration  8: sum of abs. weighted deviations =  1038.3215
Iteration  9: sum of abs. weighted deviations =  1026.7975
Iteration 10: sum of abs. weighted deviations =  1012.0173
Iteration 11: sum of abs. weighted deviations =  1004.2871
Iteration 12: sum of abs. weighted deviations =  998.92016
Iteration 13: sum of abs. weighted deviations =  988.56745
Iteration 14: sum of abs. weighted deviations =    978.939
Iteration 15: sum of abs. weighted deviations =   968.5154
Iteration 16: sum of abs. weighted deviations =  963.66462
Iteration 17: sum of abs. weighted deviations =  945.70324
note:  alternate solutions exist
Iteration 18: sum of abs. weighted deviations =  941.22011
Iteration 19: sum of abs. weighted deviations =  938.76969
Iteration 20: sum of abs. weighted deviations =  936.42816
Iteration 21: sum of abs. weighted deviations =   935.3478
note:  alternate solutions exist
Iteration 22: sum of abs. weighted deviations =  934.11759
Iteration 23: sum of abs. weighted deviations =  932.82746
note:  alternate solutions exist
```

```
Iteration 24: sum of abs. weighted deviations =  931.43069
note:  alternate solutions exist
Iteration 25: sum of abs. weighted deviations =  929.24336
Iteration 26: sum of abs. weighted deviations =  927.78956
Iteration 27: sum of abs. weighted deviations =  927.22901
Iteration 28: sum of abs. weighted deviations =  926.06536
Iteration 29: sum of abs. weighted deviations =  925.35384
Iteration 30: sum of abs. weighted deviations =  924.70198
Iteration 31: sum of abs. weighted deviations =  924.21811
Iteration 32: sum of abs. weighted deviations =  924.16892
Iteration 33: sum of abs. weighted deviations =  924.06503

.25 Quantile regression                          Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations  924.065                 Pseudo R2     =    0.2655
```

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
badacsony	1.457481	.0093349	156.13	0.000	1.439177	1.475786
balaton	.828289	.0093495	88.59	0.000	.809956	.8466221
bb	1.147084	.0080662	142.21	0.000	1.131267	1.1629
bfelv	1.458148	.0138205	105.51	0.000	1.431048	1.485249
bfcs	1.451459	.0087356	166.15	0.000	1.43433	1.468589
bukk	1.64047	.0218068	75.23	0.000	1.59771	1.68323
duna	1.052683	.0136262	77.25	0.000	1.025964	1.079402
dunantuli	.5401897	.0087911	61.45	0.000	.5229516	.5574279
dtk	-.1546283	.0089668	-17.24	0.000	-.172211	-.1370455
eclass	1.042633	.0083116	125.44	0.000	1.026335	1.058931
esup	1.948771	.0141959	137.28	0.000	1.920935	1.976608
egs	2.438977	.0203328	119.95	0.000	2.399107	2.478847
ens10e	2.081945	.0152965	136.11	0.000	2.051951	2.11194
etyekbuda	1.234171	.0098507	125.29	0.000	1.214855	1.253487
fm	.9462109	.0086118	109.87	0.000	.9293243	.9630974
hb	1.052683	.01142	92.18	0.000	1.03029	1.075076
kali	2.082303	.0226223	92.05	0.000	2.037943	2.126662
kunsag	1.052683	.0089941	117.04	0.000	1.035047	1.07032
matra	.7636671	.0084109	90.79	0.000	.7471744	.7801598
mor	1.234171	.0148468	83.13	0.000	1.205058	1.263283
nsomlo	1.457481	.0107436	135.66	0.000	1.436415	1.478548
neszmely	1.234171	.0124791	98.90	0.000	1.209701	1.258641
pannon	1.147084	.0157594	72.79	0.000	1.116182	1.177986
phalma	1.583312	.0138258	114.52	0.000	1.556201	1.610422
pecs	1.147994	.0104103	110.27	0.000	1.12758	1.168407
sopron	1.458148	.0094481	154.33	0.000	1.439622	1.476675
szekszard	1.43112	.007273	196.77	0.000	1.416859	1.445381
tbk	2.455097	.0090755	270.52	0.000	2.437301	2.472893
tnbk	1.389155	.0074999	185.22	0.000	1.374449	1.403862
tolna	1.042633	.012668	82.30	0.000	1.017793	1.067473
vclass	1.314278	.0073867	177.93	0.000	1.299794	1.328762
vprem	2.225165	.0089438	248.79	0.000	2.207628	2.242703
zala	1.314278	.0203328	64.64	0.000	1.274408	1.354148
_cons	5.855072	.0063828	917.32	0.000	5.842556	5.867588

```
. estimates store qk25

.
. *0,5 KÜLÖN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs
ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron
szekszard tbk tnbk tolna vclass vprem zala, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  1224.2105

Iteration  1: sum of abs. weighted deviations =  1222.5408
Iteration  2: sum of abs. weighted deviations =  1221.4876
Iteration  3: sum of abs. weighted deviations =  1221.3692
Iteration  4: sum of abs. weighted deviations =  1221.2896
Iteration  5: sum of abs. weighted deviations =  1220.5399
Iteration  6: sum of abs. weighted deviations =  1219.6576
Iteration  7: sum of abs. weighted deviations =  1219.2512
Iteration  8: sum of abs. weighted deviations =  1218.6243
Iteration  9: sum of abs. weighted deviations =  1218.2562
Iteration 10: sum of abs. weighted deviations =  1218.1755
Iteration 11: sum of abs. weighted deviations =   1218.062
Iteration 12: sum of abs. weighted deviations =   1217.299
Iteration 13: sum of abs. weighted deviations =  1217.2931
```

```
Iteration 14: sum of abs. weighted deviations =  1217.2931
Iteration 15: sum of abs. weighted deviations =  1217.0861
Iteration 16: sum of abs. weighted deviations =   1216.877
note:  alternate solutions exist
Iteration 17: sum of abs. weighted deviations =  1216.8025
note:  alternate solutions exist
Iteration 18: sum of abs. weighted deviations =  1216.7095
note:  alternate solutions exist
Iteration 19: sum of abs. weighted deviations =  1216.7095
note:  alternate solutions exist
Iteration 20: sum of abs. weighted deviations =  1216.6974
Iteration 21: sum of abs. weighted deviations =  1216.6835
Iteration 22: sum of abs. weighted deviations =  1216.5702
Iteration 23: sum of abs. weighted deviations =  1216.5702
Iteration 24: sum of abs. weighted deviations =  1216.5453

Median regression                                    Number of obs =      2672
  Raw sum of deviations 1572.158 (about 7.4024515)
  Min sum of deviations 1216.545                     Pseudo R2     =    0.2262
```

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
badacsony	.8484097	.016563	51.22	0.000	.8159319	.8808874
balaton	.3680673	.0167134	22.02	0.000	.3352945	.40084
bb	.5112705	.0144645	35.35	0.000	.4829076	.5396334
bfelv	.6371007	.02426	26.26	0.000	.5895301	.6846713
bfcs	.6937032	.0155502	44.61	0.000	.6632114	.724195
bukk	.6942592	.0380299	18.26	0.000	.6196878	.7688306
duna	.4065771	.0421182	9.65	0.000	.323989	.4891652
dunantuli	4.25e-13	.0165611	0.00	1.000	-.0324741	.0324741
dtk	-.8904862	.0159018	-56.00	0.000	-.9216674	-.8593051
eclass	.5112705	.014625	34.96	0.000	.482593	.5399481
esup	1.541557	.0246293	62.59	0.000	1.493263	1.589852
egs	1.711903	.0397494	43.07	0.000	1.633959	1.789846
ens10e	1.467449	.0274684	53.42	0.000	1.413587	1.521311
etyekbuda	.4422302	.0173425	25.50	0.000	.4082239	.4762365
fm	.4641466	.0154318	30.08	0.000	.433887	.4944062
hb	.3207769	.0205695	15.59	0.000	.2804429	.361111
kali	1.198396	.0421182	28.45	0.000	1.115808	1.280984
kunsag	.3296161	.0160331	20.56	0.000	.2981774	.3610547
matra	.2804255	.0149689	18.73	0.000	.2510736	.3097775
mor	.5112705	.0292881	17.46	0.000	.4538405	.5687005
nsomlo	.8949299	.0202422	44.21	0.000	.8552376	.9346222
neszmely	.4422302	.0212063	20.85	0.000	.4006476	.4838128
pannon	.4065771	.028083	14.48	0.000	.3515102	.461644
phalma	.7991195	.0250231	31.94	0.000	.7500526	.8481863
pecs	.5119376	.0191986	26.67	0.000	.4742919	.5495834
sopron	.7639923	.0175786	43.46	0.000	.729523	.7984616
szekszard	.7430491	.0131536	56.49	0.000	.7172566	.7688416
tbk	2.181529	.016157	135.02	0.000	2.149847	2.213211
tnbk	.9393816	.0134911	69.63	0.000	.9129273	.9658359
tolna	.4780359	.0216713	22.06	0.000	.4355414	.5205304
vclass	.575851	.0133132	43.25	0.000	.5497456	.6019563
vprem	1.711903	.0159597	107.26	0.000	1.680608	1.743197
zala	.575851	.0365961	15.74	0.000	.504091	.6476109
_cons	6.801283	.0116435	584.13	0.000	6.778452	6.824114

```
. estimates store qk50

.
. *0,75 KÜLÖN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs
ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron
szekszard tbk tnbk tolna vclass vprem zala, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  1164.8431

Iteration  1: sum of abs. weighted deviations =  1175.2984
Iteration  2: sum of abs. weighted deviations =  1160.4561
Iteration  3: sum of abs. weighted deviations =  1150.0745
note:  alternate solutions exist
Iteration  4: sum of abs. weighted deviations =  1129.3907
Iteration  5: sum of abs. weighted deviations =  1114.0675
Iteration  6: sum of abs. weighted deviations =  1105.3557
Iteration  7: sum of abs. weighted deviations =  1102.0245
Iteration  8: sum of abs. weighted deviations =  1097.3956
```

```
Iteration  9: sum of abs. weighted deviations =  1092.6827
Iteration 10: sum of abs. weighted deviations =  1078.6209
Iteration 11: sum of abs. weighted deviations =  1066.4354
Iteration 12: sum of abs. weighted deviations =  1063.6149
note:  alternate solutions exist
Iteration 13: sum of abs. weighted deviations =  1060.4191
Iteration 14: sum of abs. weighted deviations =  1054.2916
note:  alternate solutions exist
Iteration 15: sum of abs. weighted deviations =  1049.8713
Iteration 16: sum of abs. weighted deviations =  1043.2938
Iteration 17: sum of abs. weighted deviations =  1039.1792
Iteration 18: sum of abs. weighted deviations =  1032.4861
Iteration 19: sum of abs. weighted deviations =  1031.3537
Iteration 20: sum of abs. weighted deviations =  1028.3618
note:  alternate solutions exist
Iteration 21: sum of abs. weighted deviations =  1027.6758
note:  alternate solutions exist
Iteration 22: sum of abs. weighted deviations =  1026.5542
Iteration 23: sum of abs. weighted deviations =  1025.3096
Iteration 24: sum of abs. weighted deviations =  1024.4104
Iteration 25: sum of abs. weighted deviations =  1023.0848
Iteration 26: sum of abs. weighted deviations =  1022.2634
note:  alternate solutions exist
Iteration 27: sum of abs. weighted deviations =  1021.0188
Iteration 28: sum of abs. weighted deviations =  1020.0643
Iteration 29: sum of abs. weighted deviations =  1020.0609
Iteration 30: sum of abs. weighted deviations =  1019.8796
Iteration 31: sum of abs. weighted deviations =  1019.4682
Iteration 32: sum of abs. weighted deviations =  1019.0562
Iteration 33: sum of abs. weighted deviations =  1018.6144
Iteration 34: sum of abs. weighted deviations =  1018.5415
Iteration 35: sum of abs. weighted deviations =  1018.1999

.75 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations   1018.2                    Pseudo R2     =    0.2573

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .4567585   .0974967     4.68   0.000     .2655807    .6479363
     balaton |  -.0380845   .0977514    -0.39   0.697    -.2297616    .1535926
          bb |   .1466036   .0848863     1.73   0.084    -.0198468     .313054
       bfelv |  -.0159154   .1339967    -0.12   0.905    -.2786647    .2468339
        bfcs |    .274437   .0915133     3.00   0.003     .0949919     .453882
        bukk |   .0462809   .2320586     0.20   0.842    -.4087543    .5013161
        duna |   .1000834   .2320586     0.43   0.666    -.3549519    .5551186
   dunantuli |  -.2370558   .0968803    -2.45   0.014    -.4270249   -.0470867
         dtk |  -1.154347   .0941547   -12.26   0.000    -1.338972   -.9697229
      eclass |   .0612435   .0873767     0.70   0.483    -.1100902    .2325773
        esup |   1.088916    .146462     7.43   0.000     .8017238    1.376108
         egs |   1.660731   .2087593     7.96   0.000     1.251383     2.07008
      ens10e |   1.013035   .1589382     6.37   0.000     .7013787    1.324691
   etyekbuda |  -.0005264   .1034186    -0.01   0.996    -.2033161    .2022633
          fm |   .1668515   .0905109     1.84   0.065    -.0106281    .3443311
          hb |  -.2373891   .1216198    -1.95   0.051    -.4758689    .0010907
        kali |   .8620014   .2320586     3.71   0.000     .4069662    1.317037
      kunsag |  -.2370558   .0921042    -2.57   0.010    -.4176596   -.0564519
       matra |  -.1724753   .0879438    -1.96   0.050    -.3449211   -.0000295
         mor |  -.2363887   .1702505    -1.39   0.165    -.5702267    .0974493
      nsomlo |   .5936174   .1150289     5.16   0.000     .3680615    .8191734
    neszmely |  -.0272088     .12467    -0.22   0.827    -.2716696     .217252
      pannon |  -.2430778   .1651816    -1.47   0.141    -.5669764    .0808209
      phalma |    .274437   .1254301     2.19   0.029     .0284855    .5203884
        pecs |  -.0005264   .1163594    -0.00   0.996    -.2286913    .2276385
      sopron |   .6109095   .1025504     5.96   0.000     .4098222    .8119967
   szekszard |   .3550949   .0771104     4.61   0.000     .2038918     .506298
         tbk |   2.161507   .0949045    22.78   0.000     1.975412    2.347601
        tnbk |   .7318621   .0792426     9.24   0.000     .5764781     .887246
       tolna |  -.1532741   .1315205    -1.17   0.244    -.4111678    .1046197
      vclass |   .1461487   .0779663     1.87   0.061    -.0067327    .2990301
       vprem |   1.344649   .0922154    14.58   0.000     1.163827    1.525471
        zala |   .0671668   .2087593     0.32   0.748    -.3421818    .4765154
       _cons |   7.549609    .068263   110.60   0.000     7.415755    7.683464
------------------------------------------------------------------------------

. estimates store qk75
```

```
.
. *0,9 KÜLÖN
. qreg logp badacsony balaton bb bfelv bfcs bukk duna dunantul dtk eclass esup egs
ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmely pannon phalma pecs sopron
szekszard tbk tnbk tolna vclass vprem zala, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  1052.8026

Iteration  1: sum of abs. weighted deviations =  1084.9297
Iteration  2: sum of abs. weighted deviations =  1026.4377
Iteration  3: sum of abs. weighted deviations =  988.40631
Iteration  4: sum of abs. weighted deviations =  925.91757
Iteration  5: sum of abs. weighted deviations =   889.7886
Iteration  6: sum of abs. weighted deviations =  872.73549
Iteration  7: sum of abs. weighted deviations =  850.28741
Iteration  8: sum of abs. weighted deviations =  830.16081
Iteration  9: sum of abs. weighted deviations =  820.84501
Iteration 10: sum of abs. weighted deviations =  782.71514
Iteration 11: sum of abs. weighted deviations =   752.9855
Iteration 12: sum of abs. weighted deviations =  732.44038
Iteration 13: sum of abs. weighted deviations =  712.07306
Iteration 14: sum of abs. weighted deviations =     700.63
Iteration 15: sum of abs. weighted deviations =  685.64606
Iteration 16: sum of abs. weighted deviations =  671.25192
Iteration 17: sum of abs. weighted deviations =  653.84313
Iteration 18: sum of abs. weighted deviations =  640.18015
Iteration 19: sum of abs. weighted deviations =  627.15272
Iteration 20: sum of abs. weighted deviations =  616.62486
note:  alternate solutions exist
Iteration 21: sum of abs. weighted deviations =  612.80013
Iteration 22: sum of abs. weighted deviations =  609.60454
Iteration 23: sum of abs. weighted deviations =  606.48992
Iteration 24: sum of abs. weighted deviations =  604.67967
Iteration 25: sum of abs. weighted deviations =  603.57341
Iteration 26: sum of abs. weighted deviations =  600.78873
Iteration 27: sum of abs. weighted deviations =  597.00189
Iteration 28: sum of abs. weighted deviations =  593.87613
Iteration 29: sum of abs. weighted deviations =  593.02767
Iteration 30: sum of abs. weighted deviations =  592.10708
Iteration 31: sum of abs. weighted deviations =  591.09755
Iteration 32: sum of abs. weighted deviations =  589.49374
Iteration 33: sum of abs. weighted deviations =  587.91963
Iteration 34: sum of abs. weighted deviations =  587.19999
Iteration 35: sum of abs. weighted deviations =   584.8989

.9 Quantile regression                              Number of obs =      2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 584.8989                    Pseudo R2     =    0.3027

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   badacsony |   .2836084   .1656519     1.71   0.087    -.0412124    .6084292
     balaton |  -.2137032   .1696835    -1.26   0.208    -.5464293     .119023
          bb |  -.0163937   .1437257    -0.11   0.909    -.2982202    .2654329
       bfelv |   -.517169   .2317538    -2.23   0.026    -.9716066   -.0627314
        bfcs |  -.0057077   .1545198    -0.04   0.971    -.3086999    .2972845
        bukk |   .0267391   .1800711     0.15   0.882    -.3263558    .3798341
        duna |  -.1424761   .1800711    -0.79   0.429     -.495571    .2106189
   dunantuli |   -.451211   .1666153    -2.71   0.007    -.7779208   -.1245011
         dtk |  -1.497998   .1620677    -9.24   0.000    -1.815791   -1.180206
      eclass |  -.2073479   .1491071    -1.39   0.164    -.4997266    .0850309
        esup |   .7472143   .2385371     3.13   0.002     .2794757    1.214953
         egs |   1.871593   .1737111    10.77   0.000      1.53097    2.212217
      ens10e |   .8747911   .2332204     3.75   0.000     .4174776    1.332105
   etyekbuda |  -.0557251   .1747581    -0.32   0.750     -.398402    .2869518
          fm |  -.1553707   .1545125    -1.01   0.315    -.4583487    .1476072
          hb |  -.6129794   .2100613    -2.92   0.004    -1.024881   -.2010778
        kali |   .7612362   .1800711     4.23   0.000     .4081413    1.114331
      kunsag |   -.664299   .1612745    -4.12   0.000    -.9805364   -.3480616
       matra |  -.5176239   .1504391    -3.44   0.001    -.8126144   -.2226334
         mor |  -.6124792   .2786749    -2.20   0.028    -1.158923   -.0660357
      nsomlo |   .0293741   .2033428     0.14   0.885    -.3693534    .4281016
    neszmely |  -.5926766   .1924691    -3.08   0.002    -.9700824   -.2152709
      pannon |  -.7755866   .2416754    -3.21   0.001    -1.249479    -.301694
      phalma |  -.2137032   .2459768    -0.87   0.385    -.6960301    .2686238
        pecs |  -.3127451   .1949834    -1.60   0.109     -.695081    .0695908
```

```
      sopron |   .3137617   .1733884     1.81   0.070    -.0262293    .6537528
   szekszard |   .0804176   .1315886     0.61   0.541    -.1776096    .3384449
         tbk |   2.170215   .1620677    13.39   0.000     1.852422    2.488007
        tnbk |   .6193514   .1351587     4.58   0.000     .3543237    .8843791
       tolna |  -.2513146   .2227955    -1.13   0.259    -.6881862    .1855569
      vclass |  -.2103529   .1331425    -1.58   0.114    -.4714272    .0507214
       vprem |   .9959583   .1583018     6.29   0.000     .6855501    1.306367
        zala |  -.4385262   .1737111    -2.52   0.012    -.7791499   -.0979024
       _cons |   8.213382   .1158293    70.91   0.000     7.986256    8.440507
------------------------------------------------------------------------------

. estimates store qk90
```

7. Models B2.7-B6.7

```
. *0,1 KÜLÖN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmel
> y pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2 vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(10)
Iteration  1:  WLS sum of weighted deviations =  675.83863

Iteration  1: sum of abs. weighted deviations =  696.28497
Iteration  2: sum of abs. weighted deviations =  695.91866
Iteration  3: sum of abs. weighted deviations =  690.95201
Iteration  4: sum of abs. weighted deviations =  683.99993
Iteration  5: sum of abs. weighted deviations =  677.53128
Iteration  6: sum of abs. weighted deviations =  663.09232
Iteration  7: sum of abs. weighted deviations =  662.43122
Iteration  8: sum of abs. weighted deviations =  644.24455
Iteration  9: sum of abs. weighted deviations =   629.2687
Iteration 10: sum of abs. weighted deviations =   626.2163
Iteration 11: sum of abs. weighted deviations =  618.62731
Iteration 12: sum of abs. weighted deviations =  617.96319
Iteration 13: sum of abs. weighted deviations =  608.09522
Iteration 14: sum of abs. weighted deviations =  606.69935
Iteration 15: sum of abs. weighted deviations =  576.96946
Iteration 16: sum of abs. weighted deviations =  575.62651
Iteration 17: sum of abs. weighted deviations =  566.58371
Iteration 18: sum of abs. weighted deviations =  561.13598
Iteration 19: sum of abs. weighted deviations =  558.26709
Iteration 20: sum of abs. weighted deviations =  555.55058
Iteration 21: sum of abs. weighted deviations =  549.52426
Iteration 22: sum of abs. weighted deviations =  547.23411
Iteration 23: sum of abs. weighted deviations =  544.55706
Iteration 24: sum of abs. weighted deviations =  542.57059
Iteration 25: sum of abs. weighted deviations =   538.0987
Iteration 26: sum of abs. weighted deviations =  532.89503
Iteration 27: sum of abs. weighted deviations =  527.77174
Iteration 28: sum of abs. weighted deviations =  524.33812
Iteration 29: sum of abs. weighted deviations =  519.82745
Iteration 30: sum of abs. weighted deviations =  517.93648
Iteration 31: sum of abs. weighted deviations =   516.2443
Iteration 32: sum of abs. weighted deviations =  515.47282
Iteration 33: sum of abs. weighted deviations =  512.34754
Iteration 34: sum of abs. weighted deviations =  509.12194
Iteration 35: sum of abs. weighted deviations =  507.42007
Iteration 36: sum of abs. weighted deviations =  501.54282
Iteration 37: sum of abs. weighted deviations =  499.25464
Iteration 38: sum of abs. weighted deviations =  497.51138
Iteration 39: sum of abs. weighted deviations =  494.92931
Iteration 40: sum of abs. weighted deviations =  491.65502
Iteration 41: sum of abs. weighted deviations =  466.14862
Iteration 42: sum of abs. weighted deviations =  464.71363
Iteration 43: sum of abs. weighted deviations =  462.68653
Iteration 44: sum of abs. weighted deviations =  460.72154
Iteration 45: sum of abs. weighted deviations =  459.56601
Iteration 46: sum of abs. weighted deviations =  455.66683
Iteration 47: sum of abs. weighted deviations =  454.98357
Iteration 48: sum of abs. weighted deviations =  454.14709
Iteration 49: sum of abs. weighted deviations =  452.07038
Iteration 50: sum of abs. weighted deviations =  443.10597
Iteration 51: sum of abs. weighted deviations =  442.61698
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```
Iteration 52: sum of abs. weighted deviations =  440.54973
Iteration 53: sum of abs. weighted deviations =  439.38327
Iteration 54: sum of abs. weighted deviations =   437.4935
Iteration 55: sum of abs. weighted deviations =  436.70391
Iteration 56: sum of abs. weighted deviations =    435.084
Iteration 57: sum of abs. weighted deviations =  433.40376
Iteration 58: sum of abs. weighted deviations =  431.95334
Iteration 59: sum of abs. weighted deviations =   429.8048
Iteration 60: sum of abs. weighted deviations =  429.09362
Iteration 61: sum of abs. weighted deviations =  426.29436
Iteration 62: sum of abs. weighted deviations =  424.52693
Iteration 63: sum of abs. weighted deviations =  423.28774
Iteration 64: sum of abs. weighted deviations =  422.39324
Iteration 65: sum of abs. weighted deviations =  420.97507
Iteration 66: sum of abs. weighted deviations =   419.5335
Iteration 67: sum of abs. weighted deviations =  416.57286
Iteration 68: sum of abs. weighted deviations =   416.2269
Iteration 69: sum of abs. weighted deviations =  415.65366
Iteration 70: sum of abs. weighted deviations =  415.59641
Iteration 71: sum of abs. weighted deviations =  413.95239
Iteration 72: sum of abs. weighted deviations =  412.68753
Iteration 73: sum of abs. weighted deviations =  412.20308
Iteration 74: sum of abs. weighted deviations =  411.70384
Iteration 75: sum of abs. weighted deviations =  411.36851
Iteration 76: sum of abs. weighted deviations =  410.37307
Iteration 77: sum of abs. weighted deviations =  409.92883
Iteration 78: sum of abs. weighted deviations =  409.76909
Iteration 79: sum of abs. weighted deviations =  409.72223
Iteration 80: sum of abs. weighted deviations =  409.29599
Iteration 81: sum of abs. weighted deviations =  408.50256
Iteration 82: sum of abs. weighted deviations =  405.32778
Iteration 83: sum of abs. weighted deviations =  403.57541
Iteration 84: sum of abs. weighted deviations =  402.01283
Iteration 85: sum of abs. weighted deviations =  401.02853
Iteration 86: sum of abs. weighted deviations =  397.87765
Iteration 87: sum of abs. weighted deviations =  395.67286
Iteration 88: sum of abs. weighted deviations =  394.94491
Iteration 89: sum of abs. weighted deviations =  390.05215
Iteration 90: sum of abs. weighted deviations =  384.05004
Iteration 91: sum of abs. weighted deviations =  382.77988
Iteration 92: sum of abs. weighted deviations =  382.26565
Iteration 93: sum of abs. weighted deviations =  382.12267
Iteration 94: sum of abs. weighted deviations =  379.51309
Iteration 95: sum of abs. weighted deviations =  379.33307
Iteration 96: sum of abs. weighted deviations =  379.12121
Iteration 97: sum of abs. weighted deviations =  372.49223
Iteration 98: sum of abs. weighted deviations =  372.18689
Iteration 99: sum of abs. weighted deviations =  371.51729
Iteration 100: sum of abs. weighted deviations =  371.11316
Iteration 101: sum of abs. weighted deviations =  368.77827
Iteration 102: sum of abs. weighted deviations =  368.63303
Iteration 103: sum of abs. weighted deviations =  368.21706
Iteration 104: sum of abs. weighted deviations =  367.42703
Iteration 105: sum of abs. weighted deviations =  367.29417
Iteration 106: sum of abs. weighted deviations =  367.09076
Iteration 107: sum of abs. weighted deviations =  366.58001
Iteration 108: sum of abs. weighted deviations =  365.37765
Iteration 109: sum of abs. weighted deviations =  365.08662
Iteration 110: sum of abs. weighted deviations =  361.59046
Iteration 111: sum of abs. weighted deviations =  361.29067
Iteration 112: sum of abs. weighted deviations =  360.87756
Iteration 113: sum of abs. weighted deviations =  360.03789
Iteration 114: sum of abs. weighted deviations =  359.91286
Iteration 115: sum of abs. weighted deviations =  359.77182
Iteration 116: sum of abs. weighted deviations =  357.88868
Iteration 117: sum of abs. weighted deviations =  357.85639
Iteration 118: sum of abs. weighted deviations =  357.51126
Iteration 119: sum of abs. weighted deviations =  356.78398
Iteration 120: sum of abs. weighted deviations =   356.5871
Iteration 121: sum of abs. weighted deviations =  356.20209
Iteration 122: sum of abs. weighted deviations =  355.97746
Iteration 123: sum of abs. weighted deviations =  355.68662
Iteration 124: sum of abs. weighted deviations =  355.59347
Iteration 125: sum of abs. weighted deviations =   355.4956
note:  alternate solutions exist
Iteration 126: sum of abs. weighted deviations =  355.34656
Iteration 127: sum of abs. weighted deviations =  355.17835
```

```
Iteration 128: sum of abs. weighted deviations =  353.69803
Iteration 129: sum of abs. weighted deviations =  353.67526
Iteration 130: sum of abs. weighted deviations =   353.5166
Iteration 131: sum of abs. weighted deviations =  353.46111
Iteration 132: sum of abs. weighted deviations =  352.94833
Iteration 133: sum of abs. weighted deviations =  351.54505
Iteration 134: sum of abs. weighted deviations =  351.51346
Iteration 135: sum of abs. weighted deviations =  351.41681
Iteration 136: sum of abs. weighted deviations =  351.32596
Iteration 137: sum of abs. weighted deviations =  350.89441
Iteration 138: sum of abs. weighted deviations =  350.46565
Iteration 139: sum of abs. weighted deviations =   350.3557
Iteration 140: sum of abs. weighted deviations =   350.3259
Iteration 141: sum of abs. weighted deviations =  350.26078
Iteration 142: sum of abs. weighted deviations =  350.18256
Iteration 143: sum of abs. weighted deviations =  350.13561
Iteration 144: sum of abs. weighted deviations =   350.0868
Iteration 145: sum of abs. weighted deviations =  350.00876
Iteration 146: sum of abs. weighted deviations =  349.99281
Iteration 147: sum of abs. weighted deviations =  349.93735
Iteration 148: sum of abs. weighted deviations =   349.8801
Iteration 149: sum of abs. weighted deviations =    349.839
Iteration 150: sum of abs. weighted deviations =   349.4695
Iteration 151: sum of abs. weighted deviations =  349.44467
Iteration 152: sum of abs. weighted deviations =  349.18179
Iteration 153: sum of abs. weighted deviations =  349.17149
Iteration 154: sum of abs. weighted deviations =  349.06724
Iteration 155: sum of abs. weighted deviations =  349.00595
Iteration 156: sum of abs. weighted deviations =  348.91524
Iteration 157: sum of abs. weighted deviations =  348.67295
Iteration 158: sum of abs. weighted deviations =  348.56221
Iteration 159: sum of abs. weighted deviations =   348.3163
Iteration 160: sum of abs. weighted deviations =  348.27379
Iteration 161: sum of abs. weighted deviations =  348.08745
Iteration 162: sum of abs. weighted deviations =  348.06099
Iteration 163: sum of abs. weighted deviations =  348.02571
Iteration 164: sum of abs. weighted deviations =  347.99599
Iteration 165: sum of abs. weighted deviations =  347.96128
Iteration 166: sum of abs. weighted deviations =  346.58742
Iteration 167: sum of abs. weighted deviations =  345.85322
Iteration 168: sum of abs. weighted deviations =  345.74618
Iteration 169: sum of abs. weighted deviations =  345.72974
Iteration 170: sum of abs. weighted deviations =  345.71634
Iteration 171: sum of abs. weighted deviations =  345.66339
Iteration 172: sum of abs. weighted deviations =  345.62048
Iteration 173: sum of abs. weighted deviations =  345.57688
Iteration 174: sum of abs. weighted deviations =  345.53699
Iteration 175: sum of abs. weighted deviations =  345.45747
Iteration 176: sum of abs. weighted deviations =  345.45475
Iteration 177: sum of abs. weighted deviations =  345.14368
Iteration 178: sum of abs. weighted deviations =  345.14203
Iteration 179: sum of abs. weighted deviations =  343.92774
Iteration 180: sum of abs. weighted deviations =   343.8972
Iteration 181: sum of abs. weighted deviations =  343.88501
Iteration 182: sum of abs. weighted deviations =  343.84024
Iteration 183: sum of abs. weighted deviations =  343.78217
Iteration 184: sum of abs. weighted deviations =  343.75324
Iteration 185: sum of abs. weighted deviations =  343.73802
Iteration 186: sum of abs. weighted deviations =   343.7343
Iteration 187: sum of abs. weighted deviations =   343.7315
Iteration 188: sum of abs. weighted deviations =  343.71458
Iteration 189: sum of abs. weighted deviations =  343.70784
Iteration 190: sum of abs. weighted deviations =  343.69048
Iteration 191: sum of abs. weighted deviations =  343.62953
Iteration 192: sum of abs. weighted deviations =  343.55545
Iteration 193: sum of abs. weighted deviations =  343.54858
Iteration 194: sum of abs. weighted deviations =  343.28922
Iteration 195: sum of abs. weighted deviations =  343.23965
Iteration 196: sum of abs. weighted deviations =  343.23721
Iteration 197: sum of abs. weighted deviations =  343.20092
Iteration 198: sum of abs. weighted deviations =  343.16672
Iteration 199: sum of abs. weighted deviations =  343.15502
Iteration 200: sum of abs. weighted deviations =  343.15331
Iteration 201: sum of abs. weighted deviations =  343.14176
Iteration 202: sum of abs. weighted deviations =  343.13884
Iteration 203: sum of abs. weighted deviations =  343.12807
Iteration 204: sum of abs. weighted deviations =  343.12657
```

```
Iteration 205: sum of abs. weighted deviations =  343.12531
Iteration 206: sum of abs. weighted deviations =  343.11838
Iteration 207: sum of abs. weighted deviations =  343.11735
Iteration 208: sum of abs. weighted deviations =  343.11345
Iteration 209: sum of abs. weighted deviations =  343.11272
Iteration 210: sum of abs. weighted deviations =  343.10681
Iteration 211: sum of abs. weighted deviations =  343.04308
Iteration 212: sum of abs. weighted deviations =   343.0387
Iteration 213: sum of abs. weighted deviations =  343.03684
Iteration 214: sum of abs. weighted deviations =  343.03376
Iteration 215: sum of abs. weighted deviations =   343.0145
Iteration 216: sum of abs. weighted deviations =  343.00925
Iteration 217: sum of abs. weighted deviations =  342.99355
Iteration 218: sum of abs. weighted deviations =   342.9933
Iteration 219: sum of abs. weighted deviations =  342.98723
Iteration 220: sum of abs. weighted deviations =  342.97943
Iteration 221: sum of abs. weighted deviations =  342.97545
Iteration 222: sum of abs. weighted deviations =  342.95619
Iteration 223: sum of abs. weighted deviations =  342.94737
Iteration 224: sum of abs. weighted deviations =   342.9354
Iteration 225: sum of abs. weighted deviations =  342.92887
Iteration 226: sum of abs. weighted deviations =  342.91702
Iteration 227: sum of abs. weighted deviations =  342.91503
Iteration 228: sum of abs. weighted deviations =  342.91416
Iteration 229: sum of abs. weighted deviations =  342.91226
Iteration 230: sum of abs. weighted deviations =  342.90816
Iteration 231: sum of abs. weighted deviations =  342.90454
Iteration 232: sum of abs. weighted deviations =    342.904
Iteration 233: sum of abs. weighted deviations =  342.90338
Iteration 234: sum of abs. weighted deviations =  342.79855
Iteration 235: sum of abs. weighted deviations =  342.79774
Iteration 236: sum of abs. weighted deviations =   342.7785
Iteration 237: sum of abs. weighted deviations =  342.72006
Iteration 238: sum of abs. weighted deviations =  342.71957
Iteration 239: sum of abs. weighted deviations =  342.65762
Iteration 240: sum of abs. weighted deviations =  342.65309
Iteration 241: sum of abs. weighted deviations =  342.65267
Iteration 242: sum of abs. weighted deviations =  342.64885
Iteration 243: sum of abs. weighted deviations =  342.64631
Iteration 244: sum of abs. weighted deviations =  342.64602
Iteration 245: sum of abs. weighted deviations =  342.63457
Iteration 246: sum of abs. weighted deviations =  342.63417

.1 Quantile regression                              Number of obs =      2672
  Raw sum of deviations 731.4689 (about 6.5496507)
  Min sum of deviations 342.6342                    Pseudo R2     =    0.5316

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2267015   .0124311   -18.24   0.000    -.2510773   -.2023257
        cme2 |   .0000637     .00004     1.59   0.112    -.0000148    .0001421
         kor |   .0808114   .0106574     7.58   0.000     .0599136    .1017092
      fcukor |   .0039345   .0007823     5.03   0.000     .0024005    .0054684
     nfcukor |  -.0034363   .0020348    -1.69   0.091    -.0074263    .0005537
   badacsony |    .657003   .1145887     5.73   0.000     .4323096    .8816963
     balaton |   .6674587   .1184096     5.64   0.000     .4352729    .8996445
          bb |   .5011545   .1009327     4.97   0.000     .3032387    .6990702
       bfelv |   .7411616   .1604741     4.62   0.000     .4264929     1.05583
        bfcs |   .5904154   .1089537     5.42   0.000     .3767715    .8040593
        bukk |   .5516996   .1297719     4.25   0.000     .2972339    .8061652
        duna |   .3237961   .1262932     2.56   0.010     .0761517    .5714405
   dunantuli |   .5524435   .1150327     4.80   0.000     .3268795    .7780074
         dtk |  -.1117352   .1103846    -1.01   0.312     -.328185    .1047146
      eclass |   .5846719   .1049282     5.57   0.000     .3789214    .7904224
        esup |   1.013423   .1694403     5.98   0.000     .6811725    1.345673
         egs |   .6543582   .1288467     5.08   0.000     .4017067    .9070098
      ens10e |   .7174332   .1650674     4.35   0.000     .3937577    1.041109
   etyekbuda |   .6628277   .1228062     5.40   0.000      .422021    .9036345
          fm |   .4015379   .1046278     3.84   0.000     .1963766    .6066993
          hb |   .5516577   .1360683     4.05   0.000     .2848456    .8184698
        kali |   1.080208   .1289337     8.38   0.000     .8273858     1.33303
      kunsag |   .2816694   .1155443     2.44   0.015     .0551021    .5082366
       matra |   .4245957   .1061386     4.00   0.000     .2164718    .6327195
         mor |   .8564921   .1938886     4.42   0.000     .4763019    1.236682
      nsomlo |   .7351964   .1437287     5.12   0.000     .4533633    1.017029
    neszmely |   .6437547   .1576171     4.08   0.000     .3346884    .9528211
```

```
      pannon |   .6461816   .1697196     3.81   0.000     .3133837    .9789795
      phalma |   .9203194   .1730643     5.32   0.000     .5809631    1.259676
        pecs |   .7074915   .1360952     5.20   0.000     .4406266    .9743564
      sopron |   .7871497   .1215781     6.47   0.000     .5487509    1.025548
   szekszard |   .6653322   .0951978     6.99   0.000     .4786618    .8520026
         tbk |   1.033457   .1572821     6.57   0.000     .7250471    1.341866
        tnbk |   .5341525   .1015151     5.26   0.000     .3350948    .7332103
       tolna |   .2414182   .1553639     1.55   0.120    -.0632301    .5460665
      vclass |   .6347886    .096802     6.56   0.000     .4449727    .8246045
       vprem |   1.197338   .1132125    10.58   0.000     .9753435    1.419333
        zala |   .5898984   .1242448     4.75   0.000     .3462706    .8335262
        dulo |   .4314878   .0766352     5.63   0.000     .2812163    .5817593
       tier1 |   .3941191   .0429468     9.18   0.000      .309906    .4783322
       tier2 |   .2858883   .0400571     7.14   0.000     .2073415    .3644351
      vbordo |  -.0148346   .0627659    -0.24   0.813    -.1379103    .1082411
      vegyeb |  -.1652133   .0576062    -2.87   0.004    -.2781715   -.0522552
        vnem |   -.138975   .1019973    -1.36   0.173    -.3389782    .0610282
      ffajta |  -.1482012   .0500863    -2.96   0.003     -.246414   -.0499885
        fnem |  -.2305392   .1118282    -2.06   0.039    -.4498196   -.0112588
   muskegyeb |  -.1599144   .0769445    -2.08   0.038    -.3107925   -.0090363
        csfi |  -.1307616   .0821791    -1.59   0.112    -.2919039    .0303808
       _cons |   8.120256   .1506324    53.91   0.000     7.824885    8.415626
------------------------------------------------------------------------------

. estimates store qk10

.
. *0,25 KÜLÖN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmel
> y pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2 vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(25)
Iteration  1:  WLS sum of weighted deviations =  755.85112

Iteration  1: sum of abs. weighted deviations =  759.97906
Iteration  2: sum of abs. weighted deviations =  758.12769
Iteration  3: sum of abs. weighted deviations =  752.39385
Iteration  4: sum of abs. weighted deviations =   747.2645
Iteration  5: sum of abs. weighted deviations =  745.35586
Iteration  6: sum of abs. weighted deviations =  743.30494
Iteration  7: sum of abs. weighted deviations =   737.7668
Iteration  8: sum of abs. weighted deviations =  728.44717
Iteration  9: sum of abs. weighted deviations =  720.49962
Iteration 10: sum of abs. weighted deviations =  719.72434
Iteration 11: sum of abs. weighted deviations =  718.28293
Iteration 12: sum of abs. weighted deviations =  713.93197
Iteration 13: sum of abs. weighted deviations =  708.99666
Iteration 14: sum of abs. weighted deviations =  704.99153
Iteration 15: sum of abs. weighted deviations =  693.44555
Iteration 16: sum of abs. weighted deviations =  692.72474
Iteration 17: sum of abs. weighted deviations =  690.75846
Iteration 18: sum of abs. weighted deviations =  690.45654
Iteration 19: sum of abs. weighted deviations =  689.68765
Iteration 20: sum of abs. weighted deviations =  689.12234
Iteration 21: sum of abs. weighted deviations =  686.73382
Iteration 22: sum of abs. weighted deviations =  686.41601
Iteration 23: sum of abs. weighted deviations =  685.85897
Iteration 24: sum of abs. weighted deviations =  684.96426
Iteration 25: sum of abs. weighted deviations =  684.17113
Iteration 26: sum of abs. weighted deviations =   680.4977
Iteration 27: sum of abs. weighted deviations =  678.89775
Iteration 28: sum of abs. weighted deviations =   676.9741
Iteration 29: sum of abs. weighted deviations =  676.16176
Iteration 30: sum of abs. weighted deviations =  675.33497
Iteration 31: sum of abs. weighted deviations =  673.22374
Iteration 32: sum of abs. weighted deviations =  671.53699
Iteration 33: sum of abs. weighted deviations =  671.39469
Iteration 34: sum of abs. weighted deviations =  670.40921
Iteration 35: sum of abs. weighted deviations =  669.68057
Iteration 36: sum of abs. weighted deviations =  669.04542
Iteration 37: sum of abs. weighted deviations =  668.33869
Iteration 38: sum of abs. weighted deviations =  666.99655
Iteration 39: sum of abs. weighted deviations =  666.69253
Iteration 40: sum of abs. weighted deviations =    666.622
Iteration 41: sum of abs. weighted deviations =   664.2713
Iteration 42: sum of abs. weighted deviations =  663.31623
Iteration 43: sum of abs. weighted deviations =  662.67917
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Iteration 44: sum of abs. weighted deviations =   662.5391
Iteration 45: sum of abs. weighted deviations =  662.29344
Iteration 46: sum of abs. weighted deviations =  661.69143
Iteration 47: sum of abs. weighted deviations =  661.58661
note:  alternate solutions exist
Iteration 48: sum of abs. weighted deviations =  660.62046
Iteration 49: sum of abs. weighted deviations =  660.32421
Iteration 50: sum of abs. weighted deviations =  659.96884
Iteration 51: sum of abs. weighted deviations =  658.78417
Iteration 52: sum of abs. weighted deviations =  657.03732
Iteration 53: sum of abs. weighted deviations =  656.81935
Iteration 54: sum of abs. weighted deviations =  655.51385
Iteration 55: sum of abs. weighted deviations =  655.19454
Iteration 56: sum of abs. weighted deviations =  654.02494
Iteration 57: sum of abs. weighted deviations =  653.14175
Iteration 58: sum of abs. weighted deviations =  653.02287
Iteration 59: sum of abs. weighted deviations =  652.81041
Iteration 60: sum of abs. weighted deviations =  652.29411
Iteration 61: sum of abs. weighted deviations =  652.00845
Iteration 62: sum of abs. weighted deviations =  651.88765
Iteration 63: sum of abs. weighted deviations =  651.65263
Iteration 64: sum of abs. weighted deviations =  651.43939
Iteration 65: sum of abs. weighted deviations =  651.27515
Iteration 66: sum of abs. weighted deviations =  651.06505
Iteration 67: sum of abs. weighted deviations =  649.54909
Iteration 68: sum of abs. weighted deviations =  649.29853
Iteration 69: sum of abs. weighted deviations =  649.19475
Iteration 70: sum of abs. weighted deviations =  648.15526
Iteration 71: sum of abs. weighted deviations =  647.95935
Iteration 72: sum of abs. weighted deviations =  647.86358
Iteration 73: sum of abs. weighted deviations =  647.22577
Iteration 74: sum of abs. weighted deviations =  645.61881
Iteration 75: sum of abs. weighted deviations =  645.53844
Iteration 76: sum of abs. weighted deviations =  645.10569
Iteration 77: sum of abs. weighted deviations =  643.08329
Iteration 78: sum of abs. weighted deviations =  642.90142
Iteration 79: sum of abs. weighted deviations =  642.81309
note:  alternate solutions exist
Iteration 80: sum of abs. weighted deviations =  642.50969
Iteration 81: sum of abs. weighted deviations =  642.44191
Iteration 82: sum of abs. weighted deviations =  642.32914
Iteration 83: sum of abs. weighted deviations =  642.29097
Iteration 84: sum of abs. weighted deviations =  642.24279
Iteration 85: sum of abs. weighted deviations =   641.6068
Iteration 86: sum of abs. weighted deviations =  641.55827
Iteration 87: sum of abs. weighted deviations =  641.54928
Iteration 88: sum of abs. weighted deviations =  641.43893
Iteration 89: sum of abs. weighted deviations =  641.27359
Iteration 90: sum of abs. weighted deviations =  641.25306
Iteration 91: sum of abs. weighted deviations =  641.23636
Iteration 92: sum of abs. weighted deviations =  641.22069
Iteration 93: sum of abs. weighted deviations =  641.20256
Iteration 94: sum of abs. weighted deviations =   641.1685
Iteration 95: sum of abs. weighted deviations =  641.14831
Iteration 96: sum of abs. weighted deviations =  641.09723
Iteration 97: sum of abs. weighted deviations =   641.0243
Iteration 98: sum of abs. weighted deviations =  640.99066
Iteration 99: sum of abs. weighted deviations =   640.9719
Iteration 100: sum of abs. weighted deviations =  639.69799
Iteration 101: sum of abs. weighted deviations =  639.59375
Iteration 102: sum of abs. weighted deviations =  639.38487
Iteration 103: sum of abs. weighted deviations =  638.32245
Iteration 104: sum of abs. weighted deviations =  638.30998
Iteration 105: sum of abs. weighted deviations =  638.02746
Iteration 106: sum of abs. weighted deviations =  637.92219
Iteration 107: sum of abs. weighted deviations =  637.89021
Iteration 108: sum of abs. weighted deviations =   637.7904
Iteration 109: sum of abs. weighted deviations =  637.64732
Iteration 110: sum of abs. weighted deviations =  637.58459
Iteration 111: sum of abs. weighted deviations =  637.45439
Iteration 112: sum of abs. weighted deviations =  637.31328
Iteration 113: sum of abs. weighted deviations =  637.24513
Iteration 114: sum of abs. weighted deviations =  636.80373
Iteration 115: sum of abs. weighted deviations =  636.77053
Iteration 116: sum of abs. weighted deviations =  636.72344
Iteration 117: sum of abs. weighted deviations =  636.64693
Iteration 118: sum of abs. weighted deviations =  636.63634
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```
Iteration 119: sum of abs. weighted deviations =  636.60898
Iteration 120: sum of abs. weighted deviations =  636.59991
Iteration 121: sum of abs. weighted deviations =  635.84596
Iteration 122: sum of abs. weighted deviations =  635.81212
Iteration 123: sum of abs. weighted deviations =  635.76336
Iteration 124: sum of abs. weighted deviations =  635.64011
Iteration 125: sum of abs. weighted deviations =  635.51782
Iteration 126: sum of abs. weighted deviations =  635.43955
Iteration 127: sum of abs. weighted deviations =  635.40234
Iteration 128: sum of abs. weighted deviations =  635.36662
Iteration 129: sum of abs. weighted deviations =  635.35562
Iteration 130: sum of abs. weighted deviations =  635.33433
Iteration 131: sum of abs. weighted deviations =  635.33245
Iteration 132: sum of abs. weighted deviations =   634.9039
Iteration 133: sum of abs. weighted deviations =  634.89867
Iteration 134: sum of abs. weighted deviations =  634.88091
Iteration 135: sum of abs. weighted deviations =  634.86775
Iteration 136: sum of abs. weighted deviations =  634.83629
Iteration 137: sum of abs. weighted deviations =  634.82108
Iteration 138: sum of abs. weighted deviations =  634.81941
Iteration 139: sum of abs. weighted deviations =  634.81612
Iteration 140: sum of abs. weighted deviations =  634.79989
Iteration 141: sum of abs. weighted deviations =  634.79411
Iteration 142: sum of abs. weighted deviations =  634.79043
Iteration 143: sum of abs. weighted deviations =  634.77801
Iteration 144: sum of abs. weighted deviations =  634.76806
Iteration 145: sum of abs. weighted deviations =  633.91518
Iteration 146: sum of abs. weighted deviations =  633.90536
Iteration 147: sum of abs. weighted deviations =  633.89938
Iteration 148: sum of abs. weighted deviations =  633.88394
Iteration 149: sum of abs. weighted deviations =   633.8787
Iteration 150: sum of abs. weighted deviations =  633.87194
Iteration 151: sum of abs. weighted deviations =  633.84536
Iteration 152: sum of abs. weighted deviations =  633.82763
Iteration 153: sum of abs. weighted deviations =  633.82618
Iteration 154: sum of abs. weighted deviations =   633.8219
Iteration 155: sum of abs. weighted deviations =  633.81495
Iteration 156: sum of abs. weighted deviations =  633.81128
Iteration 157: sum of abs. weighted deviations =   633.7938
Iteration 158: sum of abs. weighted deviations =  633.75824
Iteration 159: sum of abs. weighted deviations =   633.7535
Iteration 160: sum of abs. weighted deviations =  633.74583
Iteration 161: sum of abs. weighted deviations =  633.72972
Iteration 162: sum of abs. weighted deviations =  633.63904
Iteration 163: sum of abs. weighted deviations =  633.63396
Iteration 164: sum of abs. weighted deviations =  633.61293
Iteration 165: sum of abs. weighted deviations =  633.60937
Iteration 166: sum of abs. weighted deviations =  633.60661
Iteration 167: sum of abs. weighted deviations =  633.60278
Iteration 168: sum of abs. weighted deviations =  633.60218
Iteration 169: sum of abs. weighted deviations =  633.59694
note:  alternate solutions exist
Iteration 170: sum of abs. weighted deviations =  633.59453
Iteration 171: sum of abs. weighted deviations =  633.59269
Iteration 172: sum of abs. weighted deviations =   633.5856
Iteration 173: sum of abs. weighted deviations =  633.58262
Iteration 174: sum of abs. weighted deviations =  633.58031
Iteration 175: sum of abs. weighted deviations =  633.58016
Iteration 176: sum of abs. weighted deviations =  633.57998
Iteration 177: sum of abs. weighted deviations =  633.56102
Iteration 178: sum of abs. weighted deviations =  633.51211
Iteration 179: sum of abs. weighted deviations =  633.51054
Iteration 180: sum of abs. weighted deviations =  633.49789
Iteration 181: sum of abs. weighted deviations =  633.49673
Iteration 182: sum of abs. weighted deviations =  633.49364
Iteration 183: sum of abs. weighted deviations =  633.49281
Iteration 184: sum of abs. weighted deviations =  633.49218
Iteration 185: sum of abs. weighted deviations =  633.47639
Iteration 186: sum of abs. weighted deviations =  633.47608
Iteration 187: sum of abs. weighted deviations =  633.47531
Iteration 188: sum of abs. weighted deviations =  633.40216
Iteration 189: sum of abs. weighted deviations =  633.33387
Iteration 190: sum of abs. weighted deviations =  633.27935
Iteration 191: sum of abs. weighted deviations =  633.27283
Iteration 192: sum of abs. weighted deviations =  633.26466
Iteration 193: sum of abs. weighted deviations =  633.25876
Iteration 194: sum of abs. weighted deviations =  633.24729
```

```
Iteration 195: sum of abs. weighted deviations =  633.24201
Iteration 196: sum of abs. weighted deviations =  633.23679
Iteration 197: sum of abs. weighted deviations =  633.23606
Iteration 198: sum of abs. weighted deviations =  633.23381
Iteration 199: sum of abs. weighted deviations =  633.23317
Iteration 200: sum of abs. weighted deviations =   633.2328
Iteration 201: sum of abs. weighted deviations =  633.21721
Iteration 202: sum of abs. weighted deviations =  633.21372
Iteration 203: sum of abs. weighted deviations =  633.21185
note:  alternate solutions exist
Iteration 204: sum of abs. weighted deviations =  633.19205
Iteration 205: sum of abs. weighted deviations =  633.19076
Iteration 206: sum of abs. weighted deviations =  633.18645
Iteration 207: sum of abs. weighted deviations =  633.18201
Iteration 208: sum of abs. weighted deviations =  633.18089
Iteration 209: sum of abs. weighted deviations =  633.17637
Iteration 210: sum of abs. weighted deviations =  633.17547
Iteration 211: sum of abs. weighted deviations =  633.17407
Iteration 212: sum of abs. weighted deviations =   633.1684
Iteration 213: sum of abs. weighted deviations =  633.16672
Iteration 214: sum of abs. weighted deviations =   633.1422
Iteration 215: sum of abs. weighted deviations =  632.89732
Iteration 216: sum of abs. weighted deviations =  632.84027
Iteration 217: sum of abs. weighted deviations =  632.83835
Iteration 218: sum of abs. weighted deviations =    632.838
Iteration 219: sum of abs. weighted deviations =  632.83781
Iteration 220: sum of abs. weighted deviations =  632.83365
Iteration 221: sum of abs. weighted deviations =  632.83361
Iteration 222: sum of abs. weighted deviations =  632.83334
Iteration 223: sum of abs. weighted deviations =  632.82915
Iteration 224: sum of abs. weighted deviations =  632.82896
Iteration 225: sum of abs. weighted deviations =  632.82894
Iteration 226: sum of abs. weighted deviations =  632.82857
Iteration 227: sum of abs. weighted deviations =  632.82857
Iteration 228: sum of abs. weighted deviations =  632.82826
Iteration 229: sum of abs. weighted deviations =   632.8282
Iteration 230: sum of abs. weighted deviations =  632.82819
Iteration 231: sum of abs. weighted deviations =  632.82817
Iteration 232: sum of abs. weighted deviations =  632.82815

.25 Quantile regression                             Number of obs =      2672
  Raw sum of deviations 1258.161 (about 7.0030656)
  Min sum of deviations 632.8281                    Pseudo R2     =    0.4970
```

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logq	-.2180464	.0085902	-25.38	0.000	-.2348906	-.2012021
cme2	.0001209	.0000465	2.60	0.009	.0000296	.0002122
kor	.1035083	.0072903	14.20	0.000	.089213	.1178035
fcukor	.0026841	.0006123	4.38	0.000	.0014835	.0038847
nfcukor	-.0053422	.0014531	-3.68	0.000	-.0081916	-.0024929
badacsony	.4559199	.081124	5.62	0.000	.2968463	.6149934
balaton	.5139049	.0797446	6.44	0.000	.3575361	.6702736
bb	.4719075	.0698055	6.76	0.000	.3350281	.608787
bfelv	.4924809	.116084	4.24	0.000	.2648555	.7201063
bfcs	.5049128	.0753327	6.70	0.000	.3571951	.6526304
bukk	.3510609	.1894569	1.85	0.064	-.0204393	.722561
duna	.2426152	.1875052	1.29	0.196	-.1250579	.6102883
dunantuli	.3818901	.0790525	4.83	0.000	.2268785	.5369018
dtk	-.3693091	.077332	-4.78	0.000	-.5209469	-.2176712
eclass	.4308772	.072885	5.91	0.000	.2879593	.5737952
esup	.808378	.1172236	6.90	0.000	.5785178	1.038238
egs	.5158796	.1704272	3.03	0.002	.1816941	.850065
ens10e	.5044268	.1328187	3.80	0.000	.2439868	.7648668
etyekbuda	.5723472	.0844441	6.78	0.000	.4067633	.737931
fm	.3780839	.0736645	5.13	0.000	.2336375	.5225303
hb	.2891542	.0972457	2.97	0.003	.0984681	.4798402
kali	1.086917	.1880177	5.78	0.000	.7182392	1.455595
kunsag	.1640415	.0778679	2.11	0.035	.0113527	.3167302
matra	.2441902	.0727475	3.36	0.001	.101542	.3868385
mor	.587845	.1413509	4.16	0.000	.3106745	.8650156
nsomlo	.6803287	.0973451	6.99	0.000	.4894477	.8712098
neszmely	.4259094	.1091145	3.90	0.000	.2119502	.6398686
pannon	.5156507	.1341933	3.84	0.000	.2525153	.7787861
phalma	.7791484	.1180293	6.60	0.000	.5477084	1.010588
pecs	.4846252	.0947191	5.12	0.000	.2988935	.6703569

```
      sopron |   .6179371    .084817     7.29   0.000     .4516221     .784252
   szekszard |   .5094653   .0652222     7.81   0.000      .381573    .6373576
         tbk |   .8067593   .1055768     7.64   0.000     .5997371    1.013781
        tnbk |   .4471882   .0681881     6.56   0.000     .3134803    .5808962
       tolna |   .1853852   .1069788     1.73   0.083    -.0243862    .3951565
      vclass |   .4953627   .0664367     7.46   0.000     .3650892    .6256363
       vprem |   .9512097   .0799465    11.90   0.000     .7944452    1.107974
        zala |   .2597515    .169493     1.53   0.126    -.0726021    .5921051
        dulo |   .3571031   .0545774     6.54   0.000     .2500839    .4641222
       tier1 |   .3966637   .0295425    13.43   0.000     .3387348    .4545926
       tier2 |   .3189923   .0275129    11.59   0.000     .2650432    .3729415
      vbordo |  -.0053141   .0448089    -0.12   0.906    -.0931785    .0825503
      vegyeb |  -.0925758    .041325    -2.24   0.025    -.1736086    -.011543
        vnem |  -.1945505   .0716686    -2.71   0.007    -.3350833   -.0540177
      ffajta |  -.1053898   .0366407    -2.88   0.004    -.1772373   -.0335423
        fnem |  -.1453977   .0771881    -1.88   0.060    -.2967533     .005958
   muskegyeb |  -.0974821   .0533765    -1.83   0.068    -.2021464    .0071822
        csfi |  -.0711979   .0571582    -1.25   0.213    -.1832776    .0408819
       _cons |   8.291816   .1038947    79.81   0.000     8.088092    8.495539
------------------------------------------------------------------------------

. estimates store qk25

.
. *0,5 KÜLÖN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmel
> y pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2 vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(50)
Iteration  1:  WLS sum of weighted deviations =  812.90112

Iteration  1: sum of abs. weighted deviations =  835.49156
Iteration  2: sum of abs. weighted deviations =  813.41257
Iteration  3: sum of abs. weighted deviations =  813.27902
Iteration  4: sum of abs. weighted deviations =  811.05027
Iteration  5: sum of abs. weighted deviations =  811.01898
Iteration  6: sum of abs. weighted deviations =   810.8906
Iteration  7: sum of abs. weighted deviations =  810.48445
Iteration  8: sum of abs. weighted deviations =   810.3907
Iteration  9: sum of abs. weighted deviations =  810.34761
Iteration 10: sum of abs. weighted deviations =   810.0587
Iteration 11: sum of abs. weighted deviations =  810.03279
Iteration 12: sum of abs. weighted deviations =  809.91187
Iteration 13: sum of abs. weighted deviations =  809.87321
Iteration 14: sum of abs. weighted deviations =   809.8018
Iteration 15: sum of abs. weighted deviations =  809.78026
Iteration 16: sum of abs. weighted deviations =  809.59282
Iteration 17: sum of abs. weighted deviations =  809.56058
Iteration 18: sum of abs. weighted deviations =  809.51881
Iteration 19: sum of abs. weighted deviations =  809.41935
Iteration 20: sum of abs. weighted deviations =   809.3773
Iteration 21: sum of abs. weighted deviations =  809.33295
Iteration 22: sum of abs. weighted deviations =  809.32498
Iteration 23: sum of abs. weighted deviations =  809.30721
Iteration 24: sum of abs. weighted deviations =  809.29616
Iteration 25: sum of abs. weighted deviations =   809.2423
Iteration 26: sum of abs. weighted deviations =  809.21669
Iteration 27: sum of abs. weighted deviations =  809.20111
Iteration 28: sum of abs. weighted deviations =  809.19094
Iteration 29: sum of abs. weighted deviations =  809.09427
note:  alternate solutions exist
Iteration 30: sum of abs. weighted deviations =  808.91532
Iteration 31: sum of abs. weighted deviations =  808.90878
Iteration 32: sum of abs. weighted deviations =  808.90615
Iteration 33: sum of abs. weighted deviations =   808.8939
Iteration 34: sum of abs. weighted deviations =  808.88349
Iteration 35: sum of abs. weighted deviations =  808.83044
Iteration 36: sum of abs. weighted deviations =  808.82649
Iteration 37: sum of abs. weighted deviations =  808.79158
Iteration 38: sum of abs. weighted deviations =  808.78831
Iteration 39: sum of abs. weighted deviations =  808.78426
Iteration 40: sum of abs. weighted deviations =   808.7793
Iteration 41: sum of abs. weighted deviations =  808.76925
Iteration 42: sum of abs. weighted deviations =  808.75911
Iteration 43: sum of abs. weighted deviations =  808.73519
Iteration 44: sum of abs. weighted deviations =   808.7161
Iteration 45: sum of abs. weighted deviations =  808.67407
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Iteration 46: sum of abs. weighted deviations =   808.6673
Iteration 47: sum of abs. weighted deviations =  808.65846
Iteration 48: sum of abs. weighted deviations =  808.56485
Iteration 49: sum of abs. weighted deviations =  808.55676
Iteration 50: sum of abs. weighted deviations =  808.54367
Iteration 51: sum of abs. weighted deviations =  808.54356
Iteration 52: sum of abs. weighted deviations =  808.54231
Iteration 53: sum of abs. weighted deviations =  808.53895
Iteration 54: sum of abs. weighted deviations =  808.53498
Iteration 55: sum of abs. weighted deviations =   808.4884
Iteration 56: sum of abs. weighted deviations =  808.48585
Iteration 57: sum of abs. weighted deviations =  808.46843
Iteration 58: sum of abs. weighted deviations =  808.44718
Iteration 59: sum of abs. weighted deviations =  808.44574
Iteration 60: sum of abs. weighted deviations =  808.44028
Iteration 61: sum of abs. weighted deviations =  808.42763
Iteration 62: sum of abs. weighted deviations =   808.4196
Iteration 63: sum of abs. weighted deviations =  808.41702
Iteration 64: sum of abs. weighted deviations =  808.41116
Iteration 65: sum of abs. weighted deviations =  808.40936
Iteration 66: sum of abs. weighted deviations =   808.4034
Iteration 67: sum of abs. weighted deviations =  808.39609
Iteration 68: sum of abs. weighted deviations =  808.39419
Iteration 69: sum of abs. weighted deviations =  808.39301
Iteration 70: sum of abs. weighted deviations =  808.39161
Iteration 71: sum of abs. weighted deviations =  808.22665
Iteration 72: sum of abs. weighted deviations =  808.20644
Iteration 73: sum of abs. weighted deviations =  808.20417
Iteration 74: sum of abs. weighted deviations =  808.20046
Iteration 75: sum of abs. weighted deviations =  808.19311
Iteration 76: sum of abs. weighted deviations =   808.1908
Iteration 77: sum of abs. weighted deviations =  808.18702
Iteration 78: sum of abs. weighted deviations =  808.18521
note:  alternate solutions exist
Iteration 79: sum of abs. weighted deviations =  808.12789
Iteration 80: sum of abs. weighted deviations =  808.12609
note:  alternate solutions exist
Iteration 81: sum of abs. weighted deviations =  808.08989
Iteration 82: sum of abs. weighted deviations =  808.08819
Iteration 83: sum of abs. weighted deviations =  808.08764
Iteration 84: sum of abs. weighted deviations =  808.07952
Iteration 85: sum of abs. weighted deviations =  808.07793
Iteration 86: sum of abs. weighted deviations =  808.07532
Iteration 87: sum of abs. weighted deviations =  808.07337
note:  alternate solutions exist
Iteration 88: sum of abs. weighted deviations =    808.041
note:  alternate solutions exist
Iteration 89: sum of abs. weighted deviations =  808.02312
Iteration 90: sum of abs. weighted deviations =  808.02165
Iteration 91: sum of abs. weighted deviations =  808.02127
Iteration 92: sum of abs. weighted deviations =  808.01744
Iteration 93: sum of abs. weighted deviations =  808.01577
Iteration 94: sum of abs. weighted deviations =  808.01548
note:  alternate solutions exist
Iteration 95: sum of abs. weighted deviations =  808.01293
Iteration 96: sum of abs. weighted deviations =  808.01211
Iteration 97: sum of abs. weighted deviations =  808.01196
Iteration 98: sum of abs. weighted deviations =  808.01149
Iteration 99: sum of abs. weighted deviations =  808.01091
Iteration 100: sum of abs. weighted deviations =  808.01058
Iteration 101: sum of abs. weighted deviations =  808.01043
Iteration 102: sum of abs. weighted deviations =   808.0078
Iteration 103: sum of abs. weighted deviations =  808.00558
Iteration 104: sum of abs. weighted deviations =  808.00542
Iteration 105: sum of abs. weighted deviations =  808.00513
Iteration 106: sum of abs. weighted deviations =  807.90541
Iteration 107: sum of abs. weighted deviations =  807.90435
Iteration 108: sum of abs. weighted deviations =  807.90358
Iteration 109: sum of abs. weighted deviations =   807.9034
Iteration 110: sum of abs. weighted deviations =  807.90334
Iteration 111: sum of abs. weighted deviations =  807.90326
Iteration 112: sum of abs. weighted deviations =  807.90319
Iteration 113: sum of abs. weighted deviations =  807.90221
Iteration 114: sum of abs. weighted deviations =  807.90219
Iteration 115: sum of abs. weighted deviations =  807.90209
Iteration 116: sum of abs. weighted deviations =  807.88882
Iteration 117: sum of abs. weighted deviations =  807.88876
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Iteration 118: sum of abs. weighted deviations = 807.88824
Iteration 119: sum of abs. weighted deviations = 807.88812
Iteration 120: sum of abs. weighted deviations = 807.88795
Iteration 121: sum of abs. weighted deviations = 807.88794
Iteration 122: sum of abs. weighted deviations = 807.88777
Iteration 123: sum of abs. weighted deviations = 807.88757
Iteration 124: sum of abs. weighted deviations = 807.88686
Iteration 125: sum of abs. weighted deviations = 807.88644
Iteration 126: sum of abs. weighted deviations = 807.88637
Iteration 127: sum of abs. weighted deviations = 807.88594
Iteration 128: sum of abs. weighted deviations = 807.88583
Iteration 129: sum of abs. weighted deviations = 807.8858
Iteration 130: sum of abs. weighted deviations = 807.8858
Iteration 131: sum of abs. weighted deviations = 807.88579
Iteration 132: sum of abs. weighted deviations = 807.88578
Iteration 133: sum of abs. weighted deviations = 807.88551
Iteration 134: sum of abs. weighted deviations = 807.88498
Iteration 135: sum of abs. weighted deviations = 807.88495
Iteration 136: sum of abs. weighted deviations = 807.88489
Iteration 137: sum of abs. weighted deviations = 807.88489
Iteration 138: sum of abs. weighted deviations = 807.88488

Median regression   Number of obs = 2672
Raw sum of deviations 1572.158 (about 7.4024515)
Min sum of deviations 807.8849   Pseudo R2 = 0.4861

logp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logq	-.2135898	.0057293	-37.28	0.000	-.2248241	-.2023555
cme2	.0001683	.0000251	6.72	0.000	.0001192	.0002174
kor	.1096679	.004935	22.22	0.000	.0999911	.1193448
fcukor	.0027861	.0004201	6.63	0.000	.0019623	.0036098
nfcukor	-.0068979	.001072	-6.43	0.000	-.0089999	-.0047959
badacsony	.2462989	.0566177	4.35	0.000	.1352789	.3573189
balaton	.2953922	.0554296	5.33	0.000	.186702	.4040823
bb	.2338757	.0489135	4.78	0.000	.1379626	.3297887
bfelv	.1399693	.0791597	1.77	0.077	-.0152524	.295191
bfcs	.31367	.0528008	5.94	0.000	.2101345	.4172054
bukk	.2156861	.1389731	1.55	0.121	-.0568219	.4881942
duna	.347148	.1382587	2.51	0.012	.0760407	.6182552
dunantuli	.073194	.0549081	1.33	0.183	-.0344737	.1808616
dtk	-.5840578	.0538375	-10.85	0.000	-.689626	-.4784896
eclass	.2707686	.0506819	5.34	0.000	.171388	.3701492
esup	.7458892	.083432	8.94	0.000	.5822901	.9094884
egs	.7988963	.1323375	6.04	0.000	.5393998	1.058393
ens10e	.2466976	.0947875	2.60	0.009	.0608318	.4325634
etyekbuda	.3544412	.0589913	6.01	0.000	.2387671	.4701153
fm	.2122262	.0513201	4.14	0.000	.1115942	.3128582
hb	.0494489	.068032	0.73	0.467	-.0839529	.1828506
kali	.6459195	.1384171	4.67	0.000	.3745018	.9173372
kunsag	-.0329266	.0545493	-0.60	0.546	-.1398905	.0740374
matra	.0044173	.0507412	0.09	0.931	-.0950796	.1039141
mor	.2506696	.1001972	2.50	0.012	.0541961	.4471431
nsomlo	.3830675	.0682687	5.61	0.000	.2492015	.5169335
neszmely	.1208456	.0750888	1.61	0.108	-.0263936	.2680848
pannon	.2853711	.0927931	3.08	0.002	.103416	.4673261
phalma	.5176593	.0833388	6.21	0.000	.3542429	.6810757
pecs	.1643537	.0660607	2.49	0.013	.0348174	.2938901
sopron	.3074845	.0595312	5.17	0.000	.1907516	.4242173
szekszard	.2994222	.0456783	6.56	0.000	.2098531	.3889914
tbk	.566057	.0679962	8.32	0.000	.4327253	.6993886
tnbk	.285651	.0477067	5.99	0.000	.1921045	.3791976
tolna	.012058	.0735375	0.16	0.870	-.1321395	.1562554
vclass	.2760406	.045832	6.02	0.000	.1861701	.3659111
vprem	.7201078	.055793	12.91	0.000	.610705	.8295107
zala	.0319777	.1312202	0.24	0.807	-.2253279	.2892833
dulo	.3593047	.0376461	9.54	0.000	.2854856	.4331238
tier1	.3809713	.0202999	18.77	0.000	.3411658	.4207767
tier2	.2916555	.0191317	15.24	0.000	.2541408	.3291703
vbordo	.0101411	.0294117	0.34	0.730	-.0475314	.0678136
vegyeb	-.0968614	.0279756	-3.46	0.001	-.1517178	-.042005
vnem	-.2158739	.0499648	-4.32	0.000	-.3138482	-.1178995
ffajta	-.0882903	.0251759	-3.51	0.000	-.1376569	-.0389236
fnem	-.0746572	.054591	-1.37	0.172	-.1817029	.0323885
muskegyeb	-.132318	.0375002	-3.53	0.000	-.2058509	-.0587851
csfi	-.0936655	.0394208	-2.38	0.018	-.1709645	-.0163664

```
       _cons |   8.651135   .0717128   120.64   0.000     8.510516    8.791755
------------------------------------------------------------------------------

. estimates store qk50

.
. *0,75 KÜLÖN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmel
> y pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2 vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(75)
Iteration  1:  WLS sum of weighted deviations =  773.67708

Iteration  1: sum of abs. weighted deviations =   816.2436
Iteration  2: sum of abs. weighted deviations =  778.84154
Iteration  3: sum of abs. weighted deviations =   775.5086
Iteration  4: sum of abs. weighted deviations =  774.08581
Iteration  5: sum of abs. weighted deviations =   768.6588
Iteration  6: sum of abs. weighted deviations =  764.35145
Iteration  7: sum of abs. weighted deviations =  759.62791
Iteration  8: sum of abs. weighted deviations =  759.37846
Iteration  9: sum of abs. weighted deviations =  754.69003
Iteration 10: sum of abs. weighted deviations =  750.79617
Iteration 11: sum of abs. weighted deviations =  748.99847
Iteration 12: sum of abs. weighted deviations =  747.86624
Iteration 13: sum of abs. weighted deviations =  743.75175
Iteration 14: sum of abs. weighted deviations =   741.6411
Iteration 15: sum of abs. weighted deviations =  740.82001
Iteration 16: sum of abs. weighted deviations =  738.16632
Iteration 17: sum of abs. weighted deviations =   732.6847
Iteration 18: sum of abs. weighted deviations =   732.5034
Iteration 19: sum of abs. weighted deviations =   731.6502
Iteration 20: sum of abs. weighted deviations =  731.05462
Iteration 21: sum of abs. weighted deviations =  728.47621
Iteration 22: sum of abs. weighted deviations =  726.04957
Iteration 23: sum of abs. weighted deviations =   723.0639
Iteration 24: sum of abs. weighted deviations =  721.53782
Iteration 25: sum of abs. weighted deviations =  715.01141
Iteration 26: sum of abs. weighted deviations =  713.65502
Iteration 27: sum of abs. weighted deviations =  712.24024
Iteration 28: sum of abs. weighted deviations =  711.74198
Iteration 29: sum of abs. weighted deviations =   710.7172
Iteration 30: sum of abs. weighted deviations =  709.96908
Iteration 31: sum of abs. weighted deviations =  709.47406
Iteration 32: sum of abs. weighted deviations =  709.19722
Iteration 33: sum of abs. weighted deviations =   708.5515
Iteration 34: sum of abs. weighted deviations =  708.48051
Iteration 35: sum of abs. weighted deviations =  706.95108
Iteration 36: sum of abs. weighted deviations =  706.11417
Iteration 37: sum of abs. weighted deviations =  703.58495
Iteration 38: sum of abs. weighted deviations =   702.1287
Iteration 39: sum of abs. weighted deviations =  701.02774
Iteration 40: sum of abs. weighted deviations =  697.98355
Iteration 41: sum of abs. weighted deviations =  697.25276
Iteration 42: sum of abs. weighted deviations =  694.83491
Iteration 43: sum of abs. weighted deviations =  694.31232
Iteration 44: sum of abs. weighted deviations =  694.21128
Iteration 45: sum of abs. weighted deviations =  693.37035
Iteration 46: sum of abs. weighted deviations =  693.13876
Iteration 47: sum of abs. weighted deviations =  692.88073
Iteration 48: sum of abs. weighted deviations =  691.71773
Iteration 49: sum of abs. weighted deviations =  691.04454
Iteration 50: sum of abs. weighted deviations =   690.9475
Iteration 51: sum of abs. weighted deviations =   689.7319
Iteration 52: sum of abs. weighted deviations =  689.45087
Iteration 53: sum of abs. weighted deviations =  685.57559
Iteration 54: sum of abs. weighted deviations =  681.71307
Iteration 55: sum of abs. weighted deviations =    681.547
Iteration 56: sum of abs. weighted deviations =  680.44507
Iteration 57: sum of abs. weighted deviations =  680.40543
Iteration 58: sum of abs. weighted deviations =  680.26775
Iteration 59: sum of abs. weighted deviations =  678.96363
Iteration 60: sum of abs. weighted deviations =  678.60551
Iteration 61: sum of abs. weighted deviations =   676.8336
Iteration 62: sum of abs. weighted deviations =  676.76427
Iteration 63: sum of abs. weighted deviations =  676.56341
Iteration 64: sum of abs. weighted deviations =  675.94467
```

```
Iteration 65: sum of abs. weighted deviations =  675.85236
Iteration 66: sum of abs. weighted deviations =  675.68916
Iteration 67: sum of abs. weighted deviations =  675.57633
Iteration 68: sum of abs. weighted deviations =  675.55287
Iteration 69: sum of abs. weighted deviations =  675.48531
Iteration 70: sum of abs. weighted deviations =  675.29429
Iteration 71: sum of abs. weighted deviations =  672.70057
Iteration 72: sum of abs. weighted deviations =  672.61871
Iteration 73: sum of abs. weighted deviations =  672.44057
Iteration 74: sum of abs. weighted deviations =  672.16034
Iteration 75: sum of abs. weighted deviations =  672.03677
Iteration 76: sum of abs. weighted deviations =  671.99203
Iteration 77: sum of abs. weighted deviations =  670.96931
Iteration 78: sum of abs. weighted deviations =    670.636
Iteration 79: sum of abs. weighted deviations =  670.39638
Iteration 80: sum of abs. weighted deviations =  669.47335
Iteration 81: sum of abs. weighted deviations =  669.43738
Iteration 82: sum of abs. weighted deviations =  669.37656
Iteration 83: sum of abs. weighted deviations =  668.87395
Iteration 84: sum of abs. weighted deviations =  667.68556
Iteration 85: sum of abs. weighted deviations =  667.65239
Iteration 86: sum of abs. weighted deviations =  667.42867
Iteration 87: sum of abs. weighted deviations =  667.23589
Iteration 88: sum of abs. weighted deviations =  667.22969
Iteration 89: sum of abs. weighted deviations =  667.18509
Iteration 90: sum of abs. weighted deviations =  667.17559
Iteration 91: sum of abs. weighted deviations =  665.89968
Iteration 92: sum of abs. weighted deviations =  665.85663
Iteration 93: sum of abs. weighted deviations =  665.82852
Iteration 94: sum of abs. weighted deviations =  665.81392
Iteration 95: sum of abs. weighted deviations =  665.79479
Iteration 96: sum of abs. weighted deviations =  665.67773
Iteration 97: sum of abs. weighted deviations =  665.61797
Iteration 98: sum of abs. weighted deviations =  665.53791
Iteration 99: sum of abs. weighted deviations =  665.48532
Iteration 100: sum of abs. weighted deviations =  665.48266
Iteration 101: sum of abs. weighted deviations =  665.46957
Iteration 102: sum of abs. weighted deviations =  664.94287
Iteration 103: sum of abs. weighted deviations =  664.83451
Iteration 104: sum of abs. weighted deviations =  664.80447
Iteration 105: sum of abs. weighted deviations =  664.78314
Iteration 106: sum of abs. weighted deviations =  664.76271
Iteration 107: sum of abs. weighted deviations =  664.74661
Iteration 108: sum of abs. weighted deviations =  664.73485
Iteration 109: sum of abs. weighted deviations =   664.7086
Iteration 110: sum of abs. weighted deviations =  664.47211
Iteration 111: sum of abs. weighted deviations =  664.24295
Iteration 112: sum of abs. weighted deviations =  664.18928
Iteration 113: sum of abs. weighted deviations =  664.17133
Iteration 114: sum of abs. weighted deviations =  664.11372
Iteration 115: sum of abs. weighted deviations =  664.10657
Iteration 116: sum of abs. weighted deviations =  664.04629
Iteration 117: sum of abs. weighted deviations =  663.98763
Iteration 118: sum of abs. weighted deviations =  663.97724
Iteration 119: sum of abs. weighted deviations =  663.91106
Iteration 120: sum of abs. weighted deviations =  663.89069
Iteration 121: sum of abs. weighted deviations =  663.87908
Iteration 122: sum of abs. weighted deviations =  663.83664
Iteration 123: sum of abs. weighted deviations =   663.7655
Iteration 124: sum of abs. weighted deviations =  663.72871
Iteration 125: sum of abs. weighted deviations =  663.70099
Iteration 126: sum of abs. weighted deviations =   663.6937
Iteration 127: sum of abs. weighted deviations =  663.68791
Iteration 128: sum of abs. weighted deviations =  663.67457
Iteration 129: sum of abs. weighted deviations =  663.58731
note:  alternate solutions exist
Iteration 130: sum of abs. weighted deviations =  663.56265
note:  alternate solutions exist
Iteration 131: sum of abs. weighted deviations =   663.5584
note:  alternate solutions exist
Iteration 132: sum of abs. weighted deviations =  663.51599
Iteration 133: sum of abs. weighted deviations =  663.51159
Iteration 134: sum of abs. weighted deviations =  663.50832
Iteration 135: sum of abs. weighted deviations =   663.4714
Iteration 136: sum of abs. weighted deviations =  663.44846
Iteration 137: sum of abs. weighted deviations =  663.42966
Iteration 138: sum of abs. weighted deviations =  663.41925
```

```
Iteration 139: sum of abs. weighted deviations =  663.41194
Iteration 140: sum of abs. weighted deviations =  663.40816
Iteration 141: sum of abs. weighted deviations =   663.4066
Iteration 142: sum of abs. weighted deviations =  663.39973
Iteration 143: sum of abs. weighted deviations =  663.22614
Iteration 144: sum of abs. weighted deviations =  663.20106
Iteration 145: sum of abs. weighted deviations =    663.151
Iteration 146: sum of abs. weighted deviations =  663.04819
Iteration 147: sum of abs. weighted deviations =  663.04437
Iteration 148: sum of abs. weighted deviations =  663.01041
Iteration 149: sum of abs. weighted deviations =  662.97189
Iteration 150: sum of abs. weighted deviations =  662.93586
Iteration 151: sum of abs. weighted deviations =  662.92513
Iteration 152: sum of abs. weighted deviations =  662.91946
Iteration 153: sum of abs. weighted deviations =  662.90321
Iteration 154: sum of abs. weighted deviations =   662.8997
Iteration 155: sum of abs. weighted deviations =  662.87136
Iteration 156: sum of abs. weighted deviations =  662.86554
Iteration 157: sum of abs. weighted deviations =  662.71571
Iteration 158: sum of abs. weighted deviations =  662.68671
Iteration 159: sum of abs. weighted deviations =  662.68491
Iteration 160: sum of abs. weighted deviations =  662.68235
Iteration 161: sum of abs. weighted deviations =  662.67963
Iteration 162: sum of abs. weighted deviations =  662.66802
Iteration 163: sum of abs. weighted deviations =  662.66251
Iteration 164: sum of abs. weighted deviations =  662.63922
Iteration 165: sum of abs. weighted deviations =  662.63064
Iteration 166: sum of abs. weighted deviations =  662.62931
Iteration 167: sum of abs. weighted deviations =  662.62529
Iteration 168: sum of abs. weighted deviations =  662.61369
Iteration 169: sum of abs. weighted deviations =  662.60719
Iteration 170: sum of abs. weighted deviations =  662.60535
Iteration 171: sum of abs. weighted deviations =  662.60439
Iteration 172: sum of abs. weighted deviations =  662.60097
Iteration 173: sum of abs. weighted deviations =  662.60041
Iteration 174: sum of abs. weighted deviations =  662.59002
Iteration 175: sum of abs. weighted deviations =  662.58899
Iteration 176: sum of abs. weighted deviations =  662.58792
Iteration 177: sum of abs. weighted deviations =  662.58665
Iteration 178: sum of abs. weighted deviations =  662.58536
Iteration 179: sum of abs. weighted deviations =  662.58414
Iteration 180: sum of abs. weighted deviations =  662.57704
Iteration 181: sum of abs. weighted deviations =  662.52655
Iteration 182: sum of abs. weighted deviations =  662.52451
Iteration 183: sum of abs. weighted deviations =  662.00011
Iteration 184: sum of abs. weighted deviations =  661.90516
Iteration 185: sum of abs. weighted deviations =  661.90398
Iteration 186: sum of abs. weighted deviations =  661.89883
Iteration 187: sum of abs. weighted deviations =  661.89878
Iteration 188: sum of abs. weighted deviations =  661.89763
Iteration 189: sum of abs. weighted deviations =  661.89596
Iteration 190: sum of abs. weighted deviations =  661.89504
Iteration 191: sum of abs. weighted deviations =  661.89426
Iteration 192: sum of abs. weighted deviations =  661.78829

.75 Quantile regression                          Number of obs =       2672
  Raw sum of deviations 1370.959 (about 7.9004512)
  Min sum of deviations 661.7883                 Pseudo R2     =     0.5173

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.2081104   .0089668   -23.21   0.000     -.225693   -.1905278
        cme2 |   .0001481   .0000345     4.30   0.000     .0000805    .0002157
         kor |   .1249581   .0073873    16.92   0.000     .1104726    .1394436
      fcukor |   .0034285   .0006791     5.05   0.000     .0020969    .0047602
     nfcukor |   -.008953    .001874    -4.78   0.000    -.0126277   -.0052784
   badacsony |    .272805   .0942775     2.89   0.004     .0879391    .4576709
     balaton |   .2765406   .0891803     3.10   0.002     .1016697    .4514115
          bb |   .1375867   .0807456     1.70   0.089    -.0207449    .2959183
       bfelv |   .1731929   .1305844     1.33   0.185     -.082866    .4292518
        bfcs |   .2054943   .0873638     2.35   0.019     .0341854    .3768032
        bukk |   .0210927   .2092095     0.10   0.920    -.3891396     .431325
        duna |   .0453684   .2083493     0.22   0.828    -.3631772     .453914
   dunantuli |   .0131519    .088333     0.15   0.882    -.1600576    .1863614
         dtk |  -.5769611   .0871079    -6.62   0.000    -.7477684   -.4061539
      eclass |   .2041491   .0830682     2.46   0.014     .0412633     .367035
```

```
        esup |   .6447152   .1350048     4.78   0.000     .3799885    .9094418
         egs |   .7709416   .1898145     4.06   0.000     .3987402    1.143143
      ens10e |   .0862392   .1509409     0.57   0.568     -.209736    .3822144
   etyekbuda |   .2647272   .0961031     2.75   0.006     .0762818    .4531727
          fm |   .1010668   .0833657     1.21   0.225    -.0624024    .2645359
          hb |   .0202213    .109489     0.18   0.853    -.1944722    .2349148
        kali |    .894352   .2090946     4.28   0.000      .484345    1.304359
     kunsag |  -.1450015   .0888936    -1.63   0.103    -.3193103    .0293073
       matra |   -.124257   .0830532    -1.50   0.135    -.2871135    .0385995
         mor |   .0549467   .1585504     0.35   0.729    -.2559498    .3658432
      nsomlo |   .3964014   .1116481     3.55   0.000     .1774741    .6153287
    neszmely |   .0301547   .1205505     0.25   0.802    -.2062291    .2665385
      pannon |   .1888147    .137658     1.37   0.170    -.0811146    .4587441
      phalma |    .428687   .1315911     3.26   0.001     .1706541      .68672
        pecs |   .0699741   .1082031     0.65   0.518     -.142198    .2821462
      sopron |   .1394711   .0978505     1.43   0.154    -.0524009    .3313432
   szekszard |   .2011482   .0756888     2.66   0.008     .0527325     .349564
         tbk |    .511654   .1044138     4.90   0.000     .3069123    .7163958
        tnbk |   .4183509   .0788708     5.30   0.000     .2636956    .5730063
       tolna |   -.014739   .1163979    -0.13   0.899     -.24298     .213502
      vclass |   .1831281   .0756826     2.42   0.016     .0347245    .3315317
       vprem |   .6749591   .0913013     7.39   0.000     .4959291     .853989
        zala |  -.2653631   .1893767    -1.40   0.161    -.6367061    .1059798
        dulo |   .2441943    .059909     4.08   0.000     .1267206    .3616681
       tier1 |   .3584698   .0317454    11.29   0.000     .2962213    .4207183
       tier2 |   .2723799    .030675     8.88   0.000     .2122302    .3325296
      vbordo |   .0863854   .0445492     1.94   0.053    -.0009697    .1737406
      vegyeb |  -.0381894   .0443205    -0.86   0.389    -.1250961    .0487174
        vnem |  -.0387898   .0792276    -0.49   0.624    -.1941448    .1165652
      ffajta |   -.081579    .039206    -2.08   0.038    -.1584568   -.0047013
        fnem |  -.0779967   .0843701    -0.92   0.355    -.2434353     .087442
   muskegyeb |  -.2221611   .0583321    -3.81   0.000    -.3365427   -.1077795
        csfi |  -.1086145    .062754    -1.73   0.084    -.2316669    .0144379
       _cons |   8.889112   .1161001    76.56   0.000     8.661455    9.116769
------------------------------------------------------------------------------

. estimates store qk75

.
. *0,9 KÜLÖN
. qreg logp logq cme2 kor fcukor nfcukor badacsony balaton bb bfelv bfcs bukk duna
dunantul dtk eclass esup egs ens10e etyekbuda fm hb kali kunsag matra mor nsomlo neszmel
> y pannon phalma pecs sopron szekszard tbk tnbk tolna vclass vprem zala dulo tier1
tier2 vbordo vegyeb vnem ffajta fnem muskegyeb csfi, quantile(90)
Iteration  1:  WLS sum of weighted deviations =  703.59643

Iteration  1: sum of abs. weighted deviations =  737.70072
Iteration  2: sum of abs. weighted deviations =  708.81427
Iteration  3: sum of abs. weighted deviations =  696.40885
Iteration  4: sum of abs. weighted deviations =  649.04663
Iteration  5: sum of abs. weighted deviations =   648.3144
Iteration  6: sum of abs. weighted deviations =  623.24075
Iteration  7: sum of abs. weighted deviations =  616.14597
Iteration  8: sum of abs. weighted deviations =  586.19377
Iteration  9: sum of abs. weighted deviations =  584.68725
Iteration 10: sum of abs. weighted deviations =  572.07934
Iteration 11: sum of abs. weighted deviations =  570.39456
Iteration 12: sum of abs. weighted deviations =  568.00631
Iteration 13: sum of abs. weighted deviations =  566.00916
Iteration 14: sum of abs. weighted deviations =  564.03378
Iteration 15: sum of abs. weighted deviations =  553.10739
Iteration 16: sum of abs. weighted deviations =  549.38828
Iteration 17: sum of abs. weighted deviations =  547.17377
Iteration 18: sum of abs. weighted deviations =  541.70124
Iteration 19: sum of abs. weighted deviations =  533.94324
Iteration 20: sum of abs. weighted deviations =  522.69195
Iteration 21: sum of abs. weighted deviations =  521.14245
Iteration 22: sum of abs. weighted deviations =  509.57349
Iteration 23: sum of abs. weighted deviations =  507.88634
Iteration 24: sum of abs. weighted deviations =  502.20474
Iteration 25: sum of abs. weighted deviations =  501.71988
Iteration 26: sum of abs. weighted deviations =  500.79216
Iteration 27: sum of abs. weighted deviations =  498.89784
Iteration 28: sum of abs. weighted deviations =  496.03019
Iteration 29: sum of abs. weighted deviations =  494.60068
Iteration 30: sum of abs. weighted deviations =  486.98572
Iteration 31: sum of abs. weighted deviations =   484.1913
```

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Iteration 32: sum of abs. weighted deviations =   478.1645
Iteration 33: sum of abs. weighted deviations =  471.83034
Iteration 34: sum of abs. weighted deviations =  459.00915
Iteration 35: sum of abs. weighted deviations =  458.31093
Iteration 36: sum of abs. weighted deviations =  458.29923
Iteration 37: sum of abs. weighted deviations =  457.43754
Iteration 38: sum of abs. weighted deviations =  453.13925
Iteration 39: sum of abs. weighted deviations =  449.37575
Iteration 40: sum of abs. weighted deviations =  447.44797
Iteration 41: sum of abs. weighted deviations =  446.87655
Iteration 42: sum of abs. weighted deviations =  442.99894
Iteration 43: sum of abs. weighted deviations =  440.09989
Iteration 44: sum of abs. weighted deviations =  437.66303
Iteration 45: sum of abs. weighted deviations =  435.33259
Iteration 46: sum of abs. weighted deviations =  435.19645
Iteration 47: sum of abs. weighted deviations =  433.99885
Iteration 48: sum of abs. weighted deviations =  433.48713
Iteration 49: sum of abs. weighted deviations =  432.69544
Iteration 50: sum of abs. weighted deviations =  431.18793
Iteration 51: sum of abs. weighted deviations =  430.46589
Iteration 52: sum of abs. weighted deviations =  430.34663
Iteration 53: sum of abs. weighted deviations =  429.17597
Iteration 54: sum of abs. weighted deviations =  427.25668
Iteration 55: sum of abs. weighted deviations =  426.51141
Iteration 56: sum of abs. weighted deviations =  424.51359
Iteration 57: sum of abs. weighted deviations =  423.87268
Iteration 58: sum of abs. weighted deviations =  423.71026
Iteration 59: sum of abs. weighted deviations =  423.50997
Iteration 60: sum of abs. weighted deviations =  421.70347
Iteration 61: sum of abs. weighted deviations =  420.80018
Iteration 62: sum of abs. weighted deviations =   420.6644
Iteration 63: sum of abs. weighted deviations =   419.8356
Iteration 64: sum of abs. weighted deviations =  414.66851
Iteration 65: sum of abs. weighted deviations =  411.45269
Iteration 66: sum of abs. weighted deviations =  410.37385
Iteration 67: sum of abs. weighted deviations =  410.25003
Iteration 68: sum of abs. weighted deviations =  404.79865
Iteration 69: sum of abs. weighted deviations =  403.54719
Iteration 70: sum of abs. weighted deviations =  402.66004
Iteration 71: sum of abs. weighted deviations =  401.86567
Iteration 72: sum of abs. weighted deviations =  401.67721
Iteration 73: sum of abs. weighted deviations =  401.28954
Iteration 74: sum of abs. weighted deviations =  401.04352
Iteration 75: sum of abs. weighted deviations =   400.2164
Iteration 76: sum of abs. weighted deviations =  400.00445
Iteration 77: sum of abs. weighted deviations =  399.57296
Iteration 78: sum of abs. weighted deviations =  398.98983
Iteration 79: sum of abs. weighted deviations =  398.47061
Iteration 80: sum of abs. weighted deviations =   397.9054
Iteration 81: sum of abs. weighted deviations =  396.56931
Iteration 82: sum of abs. weighted deviations =  396.48396
Iteration 83: sum of abs. weighted deviations =  396.46006
Iteration 84: sum of abs. weighted deviations =  395.96291
Iteration 85: sum of abs. weighted deviations =  395.42897
Iteration 86: sum of abs. weighted deviations =  395.12071
Iteration 87: sum of abs. weighted deviations =  394.61717
Iteration 88: sum of abs. weighted deviations =  392.01934
Iteration 89: sum of abs. weighted deviations =  391.48953
Iteration 90: sum of abs. weighted deviations =  390.94506
Iteration 91: sum of abs. weighted deviations =  390.27437
Iteration 92: sum of abs. weighted deviations =  390.05477
Iteration 93: sum of abs. weighted deviations =  389.58455
Iteration 94: sum of abs. weighted deviations =  389.42812
Iteration 95: sum of abs. weighted deviations =  389.28719
Iteration 96: sum of abs. weighted deviations =  387.82069
Iteration 97: sum of abs. weighted deviations =  387.17413
Iteration 98: sum of abs. weighted deviations =   387.1404
Iteration 99: sum of abs. weighted deviations =  387.06163
Iteration 100: sum of abs. weighted deviations =  387.01618
Iteration 101: sum of abs. weighted deviations =  385.80832
Iteration 102: sum of abs. weighted deviations =  385.77941
Iteration 103: sum of abs. weighted deviations =  385.70981
Iteration 104: sum of abs. weighted deviations =  385.60834
Iteration 105: sum of abs. weighted deviations =  385.57799
Iteration 106: sum of abs. weighted deviations =  385.25117
Iteration 107: sum of abs. weighted deviations =  384.95003
Iteration 108: sum of abs. weighted deviations =  384.78166
```

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Iteration 109: sum of abs. weighted deviations =  381.99392
Iteration 110: sum of abs. weighted deviations =  381.94099
Iteration 111: sum of abs. weighted deviations =  381.44564
Iteration 112: sum of abs. weighted deviations =  381.44032
Iteration 113: sum of abs. weighted deviations =  381.43478
Iteration 114: sum of abs. weighted deviations =  380.94797
Iteration 115: sum of abs. weighted deviations =  380.56152
Iteration 116: sum of abs. weighted deviations =  380.33825
Iteration 117: sum of abs. weighted deviations =  380.24942
Iteration 118: sum of abs. weighted deviations =  380.16364
Iteration 119: sum of abs. weighted deviations =  380.06063
Iteration 120: sum of abs. weighted deviations =  379.71263
Iteration 121: sum of abs. weighted deviations =  378.52922
Iteration 122: sum of abs. weighted deviations =  378.14038
Iteration 123: sum of abs. weighted deviations =  378.10877
Iteration 124: sum of abs. weighted deviations =  377.98801
Iteration 125: sum of abs. weighted deviations =  377.79199
Iteration 126: sum of abs. weighted deviations =  376.56635
Iteration 127: sum of abs. weighted deviations =   376.4679
Iteration 128: sum of abs. weighted deviations =  376.45032
note:  alternate solutions exist
Iteration 129: sum of abs. weighted deviations =  376.07112
Iteration 130: sum of abs. weighted deviations =  375.82611
Iteration 131: sum of abs. weighted deviations =  375.70608
Iteration 132: sum of abs. weighted deviations =  375.69172
Iteration 133: sum of abs. weighted deviations =  374.47979
Iteration 134: sum of abs. weighted deviations =  374.46338
Iteration 135: sum of abs. weighted deviations =  374.17437
Iteration 136: sum of abs. weighted deviations =  374.07533
Iteration 137: sum of abs. weighted deviations =  374.05673
Iteration 138: sum of abs. weighted deviations =  374.01616
Iteration 139: sum of abs. weighted deviations =  374.01443
Iteration 140: sum of abs. weighted deviations =  373.93167
Iteration 141: sum of abs. weighted deviations =  373.64289
Iteration 142: sum of abs. weighted deviations =  373.46901
Iteration 143: sum of abs. weighted deviations =  373.46436
Iteration 144: sum of abs. weighted deviations =  373.44025
Iteration 145: sum of abs. weighted deviations =   373.3737
Iteration 146: sum of abs. weighted deviations =  373.36259
Iteration 147: sum of abs. weighted deviations =  373.32722
Iteration 148: sum of abs. weighted deviations =  373.20769
Iteration 149: sum of abs. weighted deviations =  373.16657
Iteration 150: sum of abs. weighted deviations =  373.14726
Iteration 151: sum of abs. weighted deviations =  373.10512
Iteration 152: sum of abs. weighted deviations =  373.04216
Iteration 153: sum of abs. weighted deviations =  372.96815
Iteration 154: sum of abs. weighted deviations =  372.95443
Iteration 155: sum of abs. weighted deviations =   372.9264
Iteration 156: sum of abs. weighted deviations =  372.86515
Iteration 157: sum of abs. weighted deviations =  372.83284
Iteration 158: sum of abs. weighted deviations =  371.91047
Iteration 159: sum of abs. weighted deviations =   371.9064
Iteration 160: sum of abs. weighted deviations =  370.90713
Iteration 161: sum of abs. weighted deviations =  370.89644
Iteration 162: sum of abs. weighted deviations =  370.87728
Iteration 163: sum of abs. weighted deviations =  370.87432
Iteration 164: sum of abs. weighted deviations =   370.8684
Iteration 165: sum of abs. weighted deviations =  370.12536
Iteration 166: sum of abs. weighted deviations =  369.12115
Iteration 167: sum of abs. weighted deviations =   369.1199
Iteration 168: sum of abs. weighted deviations =  369.11265
Iteration 169: sum of abs. weighted deviations =  369.09982
Iteration 170: sum of abs. weighted deviations =  369.09704
Iteration 171: sum of abs. weighted deviations =  369.09233
Iteration 172: sum of abs. weighted deviations =  369.08619
Iteration 173: sum of abs. weighted deviations =  369.08584
Iteration 174: sum of abs. weighted deviations =  369.06513
Iteration 175: sum of abs. weighted deviations =  369.03935
Iteration 176: sum of abs. weighted deviations =  369.03454
Iteration 177: sum of abs. weighted deviations =  369.02192
Iteration 178: sum of abs. weighted deviations =  369.01227
Iteration 179: sum of abs. weighted deviations =  369.00865
Iteration 180: sum of abs. weighted deviations =  368.87641
Iteration 181: sum of abs. weighted deviations =  368.87545
Iteration 182: sum of abs. weighted deviations =  368.84765
Iteration 183: sum of abs. weighted deviations =  368.84547
Iteration 184: sum of abs. weighted deviations =    368.842
```

```
Iteration 185: sum of abs. weighted deviations =  368.81692
Iteration 186: sum of abs. weighted deviations =  368.81276
Iteration 187: sum of abs. weighted deviations =  368.80856
Iteration 188: sum of abs. weighted deviations =  368.80704
Iteration 189: sum of abs. weighted deviations =  368.79839
Iteration 190: sum of abs. weighted deviations =  368.79581
Iteration 191: sum of abs. weighted deviations =  368.75925
Iteration 192: sum of abs. weighted deviations =  368.22173
Iteration 193: sum of abs. weighted deviations =   368.1439
Iteration 194: sum of abs. weighted deviations =  367.98995
Iteration 195: sum of abs. weighted deviations =  367.96781
Iteration 196: sum of abs. weighted deviations =  367.82934
Iteration 197: sum of abs. weighted deviations =  367.82311
Iteration 198: sum of abs. weighted deviations =  367.80751
Iteration 199: sum of abs. weighted deviations =  367.78803
Iteration 200: sum of abs. weighted deviations =  367.77186
Iteration 201: sum of abs. weighted deviations =  367.76087
Iteration 202: sum of abs. weighted deviations =  367.73322
Iteration 203: sum of abs. weighted deviations =  367.71715
Iteration 204: sum of abs. weighted deviations =  367.69673
Iteration 205: sum of abs. weighted deviations =  367.68391
Iteration 206: sum of abs. weighted deviations =  367.67106
Iteration 207: sum of abs. weighted deviations =  367.64049
Iteration 208: sum of abs. weighted deviations =  367.61382
Iteration 209: sum of abs. weighted deviations =  367.60723
Iteration 210: sum of abs. weighted deviations =  367.58801
Iteration 211: sum of abs. weighted deviations =  367.58244
Iteration 212: sum of abs. weighted deviations =  367.57412
Iteration 213: sum of abs. weighted deviations =  367.57061
Iteration 214: sum of abs. weighted deviations =  367.56261
Iteration 215: sum of abs. weighted deviations =  367.54148
Iteration 216: sum of abs. weighted deviations =  367.53023
Iteration 217: sum of abs. weighted deviations =  367.52469
Iteration 218: sum of abs. weighted deviations =  367.52364
Iteration 219: sum of abs. weighted deviations =  367.51879
Iteration 220: sum of abs. weighted deviations =  367.50724
Iteration 221: sum of abs. weighted deviations =  367.50444
Iteration 222: sum of abs. weighted deviations =  367.50332
Iteration 223: sum of abs. weighted deviations =  367.49121
Iteration 224: sum of abs. weighted deviations =  367.47954
Iteration 225: sum of abs. weighted deviations =  367.47647
Iteration 226: sum of abs. weighted deviations =   367.4475
Iteration 227: sum of abs. weighted deviations =   367.4473
Iteration 228: sum of abs. weighted deviations =  367.44531
Iteration 229: sum of abs. weighted deviations =  367.44371
Iteration 230: sum of abs. weighted deviations =  367.43515
Iteration 231: sum of abs. weighted deviations =  367.43166
Iteration 232: sum of abs. weighted deviations =  367.42412
Iteration 233: sum of abs. weighted deviations =  367.42053
Iteration 234: sum of abs. weighted deviations =  367.41688
Iteration 235: sum of abs. weighted deviations =  367.41654
Iteration 236: sum of abs. weighted deviations =  367.41514
Iteration 237: sum of abs. weighted deviations =   367.4007
Iteration 238: sum of abs. weighted deviations =  367.39961
Iteration 239: sum of abs. weighted deviations =   367.3938
Iteration 240: sum of abs. weighted deviations =  367.39327
Iteration 241: sum of abs. weighted deviations =  367.39304
Iteration 242: sum of abs. weighted deviations =  367.36321
Iteration 243: sum of abs. weighted deviations =  367.35179
Iteration 244: sum of abs. weighted deviations =  367.35109
Iteration 245: sum of abs. weighted deviations =   367.3502
Iteration 246: sum of abs. weighted deviations =  367.34533
Iteration 247: sum of abs. weighted deviations =  367.34525
Iteration 248: sum of abs. weighted deviations =   367.3439
Iteration 249: sum of abs. weighted deviations =  367.34057

.9 Quantile regression                              Number of obs =       2672
  Raw sum of deviations  838.788 (about 8.4316349)
  Min sum of deviations 367.3406                    Pseudo R2     =     0.5621

------------------------------------------------------------------------------
        logp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logq |  -.1827273   .0093611   -19.52   0.000    -.2010832   -.1643714
        cme2 |   .0000987   .0000334     2.96   0.003     .0000333    .0001642
         kor |   .1694371    .007869    21.53   0.000     .1540071    .1848671
      fcukor |   .0039375   .0006627     5.94   0.000     .0026381    .0052369
```

```
     nfcukor |  -.0084658    .002134    -3.97   0.000    -.0126503   -.0042814
  badacsony |   .1054786   .0969563     1.09   0.277      -.08464    .2955972
    balaton |    .023941   .0936001     0.26   0.798    -.1595965    .2074785
         bb |   -.080728   .0829011    -0.97   0.330    -.2432861    .0818301
      bfelv |  -.0339227   .1076793    -0.32   0.753    -.2450677    .1772224
       bfcs |  -.0569378   .0903919    -0.63   0.529    -.2341845    .1203089
       bukk |   .4200831    .106979     3.93   0.000     .2103113     .629855
       duna |  -.1715614   .1027821    -1.67   0.095    -.3731037    .0299808
  dunantuli |  -.2572368   .0907485    -2.83   0.005    -.4351827   -.0792908
        dtk |  -.6222809   .0909759    -6.84   0.000    -.8006728   -.4438891
     eclass |  -.1516113   .0867745    -1.75   0.081    -.3217647    .0185421
       esup |   .2604037   .1337756     1.95   0.052    -.0019127    .5227201
        egs |    .694852    .105812     6.57   0.000     .4873686    .9023354
     ens10e |  -.3027152    .139365    -2.17   0.030    -.5759916   -.0294388
  etyekbuda |  -.0428944   .0993454    -0.43   0.666    -.2376977    .1519089
         fm |  -.1913075   .0873287    -2.19   0.029    -.3625476   -.0200674
         hb |  -.1737515   .1085358    -1.60   0.110     -.386576    .0390731
       kali |   .3934866   .0982581     4.00   0.000     .2008155    .5861578
     kunsag |  -.3845975    .090374    -4.26   0.000     -.561809   -.2073861
      matra |  -.3499793   .0853605    -4.10   0.000    -.5173599   -.1825987
        mor |  -.2874998   .1552025    -1.85   0.064    -.5918314    .0168319
     nsomlo |   .1479428   .1172388     1.26   0.207    -.0819471    .3778326
   neszmely |  -.2766304   .1235381    -2.24   0.025    -.5188723   -.0343885
     pannon |  -.0821482   .1343138    -0.61   0.541    -.3455199    .1812235
     phalma |   .0292026   .1355104     0.22   0.829    -.2365156    .2949208
       pecs |  -.0404077   .1118596    -0.36   0.718    -.2597496    .1789343
     sopron |  -.1394807   .1009667    -1.38   0.167    -.3374631    .0585017
  szekszard |  -.1107787   .0775986    -1.43   0.154    -.2629394     .041382
        tbk |   .2568718   .0984987     2.61   0.009     .0637288    .4500148
       tnbk |   .2474472   .0826142     3.00   0.003     .0854515    .4094429
      tolna |  -.3288569   .1239243    -2.65   0.008    -.5718562   -.0858575
     vclass |  -.1426593     .07805    -1.83   0.068    -.2957051    .0103866
      vprem |    .387589   .0936937     4.14   0.000      .203868      .57131
       zala |  -.5652605   .1011238    -5.59   0.000     -.763551   -.3669701
       dulo |   .4796089   .0596617     8.04   0.000       .36262    .5965977
      tier1 |    .414423   .0324817    12.76   0.000     .3507306    .4781154
      tier2 |   .2956941   .0322748     9.16   0.000     .2324074    .3589808
     vbordo |   .1844296   .0439051     4.20   0.000     .0983375    .2705218
     vegyeb |   .0093882   .0455498     0.21   0.837    -.0799291    .0987054
       vnem |  -.0005555   .0771143    -0.01   0.994    -.1517666    .1506555
     ffajta |  -.0805229   .0386921    -2.08   0.038    -.1563931   -.0046527
       fnem |  -.1818675   .0937527    -1.94   0.053    -.3657043    .0019693
   muskegyeb |  -.2037266   .0592551    -3.44   0.001    -.3199181   -.0875351
       csfi |  -.0987161   .0640598    -1.54   0.123    -.2243289    .0268968
      _cons |   9.027534   .1221766    73.89   0.000     8.787961    9.267106
------------------------------------------------------------------------------

. estimates store qk90

…

...
```

Appendix III. Results of the 2nd step

1. <u>Restricted models (A)</u>

```
. *Restricted models LPA
. reg lpa maxhozam

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    9.70
       Model |  1.47390485     1  1.47390485           Prob > F      =  0.0045
    Residual |  3.95130377    26  .151973222           R-squared     =  0.2717
-------------+------------------------------           Adj R-squared =  0.2437
       Total |  5.42520862    27  .200933653           Root MSE      =  .38984

------------------------------------------------------------------------------
         lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    maxhozam |  -.0296717   .0095278    -3.11   0.004    -.0492564   -.0100871
       _cons |   10.57595   .9776762    10.82   0.000     8.566312     12.5856
------------------------------------------------------------------------------

. estimates store AHE

. reg lpa szorasq

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =   14.69
       Model |  1.95884137     1  1.95884137           Prob > F      =  0.0007
    Residual |  3.46636725    26  .133321817           R-squared     =  0.3611
-------------+------------------------------           Adj R-squared =  0.3365
       Total |  5.42520862    27  .200933653           Root MSE      =  .36513

------------------------------------------------------------------------------
         lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |  -.0075902   .0019802    -3.83   0.001    -.0116605   -.0035199
       _cons |   7.686226   .0788594    97.47   0.000     7.524128    7.848324
------------------------------------------------------------------------------

. estimates store ASE

. reg lpa kataszteripont

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =   10.44
       Model |  1.55387629     1  1.55387629           Prob > F      =  0.0033
    Residual |  3.87133233    26  .148897397           R-squared     =  0.2864
-------------+------------------------------           Adj R-squared =  0.2590
       Total |  5.42520862    27  .200933653           Root MSE      =  .38587

--------------------------------------------------------------------------------
           lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
kataszteripont |    .007025   .0021746     3.23   0.003      .002555     .011495
         _cons |    5.44167   .6535943     8.33   0.000     4.098188    6.785152
--------------------------------------------------------------------------------

. estimates store APE

. reg lpa kihasznaltsag

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =   17.55
       Model |  2.18611151     1  2.18611151           Prob > F      =  0.0003
    Residual |  3.23909711    26  .124580658           R-squared     =  0.4030
-------------+------------------------------           Adj R-squared =  0.3800
       Total |  5.42520862    27  .200933653           Root MSE      =  .35296

-------------------------------------------------------------------------------
          lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
kihasznaltsag |   .0258431   .0061693     4.19   0.000      .013162    .0385242
        _cons |    6.99469   .1462495    47.83   0.000      6.69407     7.29531
-------------------------------------------------------------------------------
```

```
. estimates store AKE

.
. *Restricted models EKIT
. reg ekit maxhozam

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    6.29
       Model |  4748.66919     1  4748.66919           Prob > F      =  0.0187
    Residual |  19633.1427    26  755.120871           R-squared     =  0.1948
-------------+------------------------------           Adj R-squared =  0.1638
       Total |  24381.8118    27  903.030068           Root MSE      =  27.479

------------------------------------------------------------------------------
        ekit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    maxhozam |  -1.684203   .6716092    -2.51   0.019    -3.064715   -.3036902
       _cons |   301.2649   68.91595     4.37   0.000     159.6061    442.9237
------------------------------------------------------------------------------

. estimates store RHE

. reg ekit szorasq

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    5.98
       Model |  4558.50477     1  4558.50477           Prob > F      =  0.0216
    Residual |  19823.3071    26  762.434887           R-squared     =  0.1870
-------------+------------------------------           Adj R-squared =  0.1557
       Total |  24381.8118    27  903.030068           Root MSE      =  27.612

------------------------------------------------------------------------------
        ekit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |  -.3661551    .149746    -2.45   0.022    -.6739625   -.0583478
       _cons |   135.9938   5.963541    22.80   0.000     123.7355     148.252
------------------------------------------------------------------------------

. estimates store RSE

. reg ekit kataszteripont

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =   10.95
       Model |  7226.39073     1  7226.39073           Prob > F      =  0.0027
    Residual |  17155.4211    26  659.823889           R-squared     =  0.2964
-------------+------------------------------           Adj R-squared =  0.2693
       Total |  24381.8118    27  903.030068           Root MSE      =  25.687

--------------------------------------------------------------------------------
          ekit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
kataszteripont |   .4790725    .144762     3.31   0.003       .18151     .776635
         _cons |  -14.15381   43.50896    -0.33   0.748    -103.5878    75.28014
--------------------------------------------------------------------------------

. estimates store RPE

. reg ekit kihasznaltsag

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    6.68
       Model |  4984.92528     1  4984.92528           Prob > F      =  0.0157
    Residual |  19396.8866    26  746.034098           R-squared     =  0.2045
-------------+------------------------------           Adj R-squared =  0.1739
       Total |  24381.8118    27  903.030068           Root MSE      =  27.314

-------------------------------------------------------------------------------
         ekit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
kihasznaltsag |   1.234065   .4774061     2.58   0.016     .2527425    2.215387
        _cons |      102.9   11.31745     9.09   0.000     79.63664    126.1633
-------------------------------------------------------------------------------

. estimates store RKE
```

```
.
. *Restricted models QE50
. reg qe50 maxhozam

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    5.36
       Model |  3415.09268     1  3415.09268           Prob > F      =  0.0287
    Residual |  16550.5931    26  636.561275           R-squared     =  0.1710
-------------+------------------------------           Adj R-squared =  0.1392
       Total |  19965.6858    27  739.469845           Root MSE      =   25.23

------------------------------------------------------------------------------
        qe50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    maxhozam |  -1.428268   .6166354    -2.32   0.029     -2.69578   -.1607554
       _cons |   270.5878   63.27492     4.28   0.000     140.5243    400.6513
------------------------------------------------------------------------------

. estimates store QHE

. reg qe50 szorasq

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    8.23
       Model |  4801.52444     1  4801.52444           Prob > F      =  0.0081
    Residual |  15164.1614    26  583.236976           R-squared     =  0.2405
-------------+------------------------------           Adj R-squared =  0.2113
       Total |  19965.6858    27  739.469845           Root MSE      =   24.15

------------------------------------------------------------------------------
        qe50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |  -.3757885   .1309714    -2.87   0.008    -.6450041    -.106573
       _cons |     131.69   5.215853    25.25   0.000     120.9687    142.4113
------------------------------------------------------------------------------

. estimates store QSE

. reg qe50 kataszteripont

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =   11.52
       Model |  6130.64166     1  6130.64166           Prob > F      =  0.0022
    Residual |  13835.0442    26  532.117083           R-squared     =  0.3071
-------------+------------------------------           Adj R-squared =  0.2804
       Total |  19965.6858    27  739.469845           Root MSE      =  23.068

--------------------------------------------------------------------------------
          qe50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
kataszteripont |   .4412589   .1300002     3.39   0.002     .1740396    .7084782
         _cons |  -7.349187   39.07224    -0.19   0.852    -87.66332    72.96495
--------------------------------------------------------------------------------

. estimates store QPE

. reg qe50 kihasznaltsag

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  1,    26) =    7.48
       Model |  4461.79813     1  4461.79813           Prob > F      =  0.0111
    Residual |  15503.8877    26  596.303373           R-squared     =  0.2235
-------------+------------------------------           Adj R-squared =  0.1936
       Total |  19965.6858    27  739.469845           Root MSE      =  24.419

-------------------------------------------------------------------------------
         qe50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
kihasznaltsag |   1.167518   .4268176     2.74   0.011      .290182    2.044854
        _cons |   99.81443   10.11819     9.86   0.000     79.01619    120.6127
-------------------------------------------------------------------------------

. estimates store QKE
```

2. Restricted models (B)

```
. *Restricted models LPA
. reg lpa maxhozam

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =   46.23
       Model |  7.74999355     1  7.74999355           Prob > F      =  0.0000
    Residual |   5.1968198    31  .167639348           R-squared     =  0.5986
-------------+------------------------------           Adj R-squared =  0.5857
       Total |  12.9468133    32  .404587917           Root MSE      =  .40944

------------------------------------------------------------------------------
         lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    maxhozam |  -.0281454   .0041395    -6.80   0.000    -.0365879   -.0197029
       _cons |   10.41376   .4064467    25.62   0.000     9.584804    11.24271
------------------------------------------------------------------------------

. estimates store AHK

. reg lpa szorasq

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    9.42
       Model |    3.018121     1    3.018121           Prob > F      =  0.0044
    Residual |  9.92869235    31  .320280398           R-squared     =  0.2331
-------------+------------------------------           Adj R-squared =  0.2084
       Total |  12.9468133    32  .404587917           Root MSE      =  .56593

------------------------------------------------------------------------------
         lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |  -.0092054   .0029988    -3.07   0.004    -.0153214   -.0030894
       _cons |    7.86059   .1126263    69.79   0.000     7.630888    8.090293
------------------------------------------------------------------------------

. estimates store ASK

. reg lpa kataszteripont

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    9.48
       Model |  3.03165476     1  3.03165476           Prob > F      =  0.0043
    Residual |  9.91515858    31  .319843825           R-squared     =  0.2342
-------------+------------------------------           Adj R-squared =  0.2095
       Total |  12.9468133    32  .404587917           Root MSE      =  .56555

--------------------------------------------------------------------------------
           lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
kataszteripont |   .0094113   .0030569     3.08   0.004     .0031767    .0156458
         _cons |   4.852263   .9279482     5.23   0.000     2.959701    6.744826
--------------------------------------------------------------------------------

. estimates store APK

. reg lpa kihasznaltsag

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =   16.53
       Model |  4.50285194     1  4.50285194           Prob > F      =  0.0003
    Residual |  8.44396141    31  .272385852           R-squared     =  0.3478
-------------+------------------------------           Adj R-squared =  0.3268
       Total |  12.9468133    32  .404587917           Root MSE      =  .52191

-------------------------------------------------------------------------------
          lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
kihasznaltsag |    .031986    .007867     4.07   0.000     .0159412    .0480308
        _cons |   6.961468   .2015661    34.54   0.000     6.550372    7.372565
-------------------------------------------------------------------------------

. estimates store AKK

.
```

```
. *Restricted models KKIT
. reg kkit maxhozam

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =   21.31
       Model |  18579.6906     1  18579.6906           Prob > F      =  0.0001
    Residual |  27024.7378    31  871.765736           R-squared     =  0.4074
-------------+------------------------------           Adj R-squared =  0.3883
       Total |  45604.4284    32  1425.13839           Root MSE      =  29.526

------------------------------------------------------------------------------
        kkit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    maxhozam |  -1.378084   .2985083    -4.62   0.000    -1.986896   -.7692726
       _cons |   270.5661   29.30998     9.23   0.000      210.788    330.3442
------------------------------------------------------------------------------

. estimates store RHK

. reg kkit szorasq

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    6.40
       Model |  7801.93539     1  7801.93539           Prob > F      =  0.0167
    Residual |   37802.493    31  1219.43526           R-squared     =  0.1711
-------------+------------------------------           Adj R-squared =  0.1443
       Total |  45604.4284    32  1425.13839           Root MSE      =   34.92

------------------------------------------------------------------------------
        kkit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |  -.4680328   .1850353    -2.53   0.017    -.8454147   -.0906509
       _cons |   145.8702   6.949508    20.99   0.000     131.6966    160.0439
------------------------------------------------------------------------------

. estimates store RSK

. reg kkit kataszteripont

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    9.47
       Model |  10670.4583     1  10670.4583           Prob > F      =  0.0043
    Residual |  34933.9701    31  1126.90226           R-squared     =  0.2340
-------------+------------------------------           Adj R-squared =  0.2093
       Total |  45604.4284    32  1425.13839           Root MSE      =  33.569

--------------------------------------------------------------------------------
          kkit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
kataszteripont |   .5583406   .1814474     3.08   0.004     .1882762    .9284051
         _cons |  -31.18301    55.0805    -0.57   0.575    -143.5204     81.1544
--------------------------------------------------------------------------------

. estimates store RPK

. reg kkit kihasznaltsag

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =   12.69
       Model |  13246.6048     1  13246.6048           Prob > F      =  0.0012
    Residual |  32357.8236    31  1043.80076           R-squared     =  0.2905
-------------+------------------------------           Adj R-squared =  0.2676
       Total |  45604.4284    32  1425.13839           Root MSE      =  32.308

-------------------------------------------------------------------------------
         kkit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
kihasznaltsag |   1.734875   .4869951     3.56   0.001     .7416415    2.728108
        _cons |   97.67203   12.47768     7.83   0.000     72.22363    123.1204
-------------------------------------------------------------------------------

. estimates store RKK

.
. *Restricted models QK50
. reg qk50 maxhozam
```

```
      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =   33.26
       Model |   21207.893     1   21207.893           Prob > F      =  0.0000
    Residual |  19765.0803    31  637.583235           R-squared     =  0.5176
-------------+------------------------------           Adj R-squared =  0.5020
       Total |  40972.9732    32  1280.40541           Root MSE      =   25.25

------------------------------------------------------------------------------
        qk50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    maxhozam |  -1.472331   .2552848    -5.77   0.000    -1.992987   -.9516737
       _cons |   275.9307   25.06594    11.01   0.000     224.8084     327.053
------------------------------------------------------------------------------

. estimates store QHK

. reg qk50 szorasq

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    8.76
       Model |   9025.4775     1   9025.4775           Prob > F      =  0.0059
    Residual |  31947.4957    31  1030.56438           R-squared     =  0.2203
-------------+------------------------------           Adj R-squared =  0.1951
       Total |  40972.9732    32  1280.40541           Root MSE      =  32.102

------------------------------------------------------------------------------
        qk50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |  -.5033965   .1701033    -2.96   0.006    -.8503245   -.1564686
       _cons |   142.7681   6.388697    22.35   0.000     129.7382    155.7979
------------------------------------------------------------------------------

. estimates store QSK

. reg qk50 kataszteripont

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    5.94
       Model |  6591.95772     1  6591.95772           Prob > F      =  0.0207
    Residual |  34381.0155    31  1109.06502           R-squared     =  0.1609
-------------+------------------------------           Adj R-squared =  0.1338
       Total |  40972.9732    32  1280.40541           Root MSE      =  33.303

--------------------------------------------------------------------------------
          qk50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
kataszteripont |   .4388488   .1800057     2.44   0.021     .0717248    .8059728
         _cons |   1.139571   54.64284     0.02   0.983    -110.3052    112.5844
--------------------------------------------------------------------------------

. estimates store QPK

. reg qk50 kihasznaltsag

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =   10.59
       Model |  10430.1903     1  10430.1903           Prob > F      =  0.0028
    Residual |  30542.7829    31  985.251063           R-squared     =  0.2546
-------------+------------------------------           Adj R-squared =  0.2305
       Total |  40972.9732    32  1280.40541           Root MSE      =  31.389

-------------------------------------------------------------------------------
         qk50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
kihasznaltsag |   1.539437   .4731396     3.25   0.003     .5744625    2.504412
        _cons |   98.39614   12.12268     8.12   0.000     73.67177    123.1205
-------------------------------------------------------------------------------

. estimates store QKK
```

3. The impact of group structure on GI rules

```
. reg maxhozam szorasq

      Source |       SS       df       MS              Number of obs =      28
```

```
-------------+------------------------------           F(  1,    26) =   17.06
       Model |  663.352084     1  663.352084           Prob > F      =  0.0003
    Residual |  1010.75506    26  38.8751946           R-squared     =  0.3962
-------------+------------------------------           Adj R-squared =  0.3730
       Total |  1674.10714    27  62.0039683           Root MSE      =   6.235

------------------------------------------------------------------------------
    maxhozam |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |   .1396774   .0338135     4.13   0.000     .0701727     .209182
       _cons |   99.62867   1.346602    73.99   0.000     96.86069    102.3966
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     28   -97.00191   -89.93776      2     183.8755    186.5399
-----------------------------------------------------------------------------


. reg maxhozam szorasq

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  1,    31) =    6.37
       Model |  1667.16167     1  1667.16167           Prob > F      =  0.0170
    Residual |  8116.17166    31  261.811989           R-squared     =  0.1704
-------------+------------------------------           Adj R-squared =  0.1436
       Total |  9783.33333    32  305.729167           Root MSE      =  16.181

------------------------------------------------------------------------------
    maxhozam |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     szorasq |   .2163535   .0857373     2.52   0.017     .0414911    .3912159
       _cons |   92.72867   3.220101    28.80   0.000     86.16123    99.29611
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     33   -140.7418   -137.6592      2     279.3185    282.3115
-----------------------------------------------------------------------------
```

4. Models C1-C3

```
. *EXTENDED MODELLEK*
. reg lpa maxhozam kihasznaltsag kataszteripont

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  3,    24) =   19.92
       Model |  3.87072893     3  1.29024298           Prob > F      =  0.0000
    Residual |  1.55447969    24  .064769987           R-squared     =  0.7135
-------------+------------------------------           Adj R-squared =  0.6777
       Total |  5.42520862    27  .200933653           Root MSE      =   .2545

--------------------------------------------------------------------------------
           lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
      maxhozam |  -.0208403   .0063881    -3.26   0.003    -.0340247   -.0076558
 kihasznaltsag |   .0203547   .0045767     4.45   0.000     .0109088    .0298006
kataszteripont |   .0050349   .0014727     3.42   0.002     .0019954    .0080744
         _cons |   7.739061    .848676     9.12   0.000      5.98748    9.490642
--------------------------------------------------------------------------------

. estimates store EAE

.
. reg ekit maxhozam kihasznaltsag kataszteripont

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  3,    24) =    9.81
       Model |  12032.5837     3  4010.86122           Prob > F      =  0.0002
```

```
    Residual |  9815.02503    24  408.959376           R-squared     =  0.5508
-------------+------------------------------           Adj R-squared =  0.4946
       Total |  21847.6087    27  809.170692           Root MSE      =  20.223

------------------------------------------------------------------------------
         ekit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     maxhozam |   -1.16548   .5076069    -2.30   0.031    -2.213129   -.1178312
 kihasznaltsag |   .8822589   .3636698     2.43   0.023     .1316812    1.632837
kataszteripont |   .3625691   .1170221     3.10   0.005     .1210473    .6040909
        _cons |   119.4595   67.43652     1.77   0.089    -19.72263    258.6416
------------------------------------------------------------------------------

. estimates store ERE

.
. reg qe50 maxhozam kihasznaltsag kataszteripont

      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  3,    24) =    7.10
       Model |  9471.73544     3  3157.24515           Prob > F      =  0.0014
    Residual |  10665.6404    24  444.401684           R-squared     =  0.4704
-------------+------------------------------           Adj R-squared =  0.4042
       Total |  20137.3759    27  745.828735           Root MSE      =  21.081

------------------------------------------------------------------------------
         qe50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     maxhozam |  -1.002302   .5291457    -1.89   0.070    -2.094405    .0898012
 kihasznaltsag |   .8983669   .3791011     2.37   0.026     .1159407    1.680793
kataszteripont |   .2931862   .1219876     2.40   0.024     .0414161    .5449563
        _cons |   117.6848   70.29799     1.67   0.107     -27.4031    262.7727
------------------------------------------------------------------------------

. estimates store EQE
```

5. Models D1-D3

```
. *EXTENDED MODELLEK*
. reg lpa maxhozam kihasznaltsag kataszteripont

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  3,    29) =   35.72
       Model |  10.1895694     3  3.39652314           Prob > F      =  0.0000
    Residual |  2.75724391    29  .095077376           R-squared     =  0.7870
-------------+------------------------------           Adj R-squared =  0.7650
       Total |  12.9468133    32  .404587917           Root MSE      =  .30835

------------------------------------------------------------------------------
          lpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     maxhozam |  -.0216692   .0033753    -6.42   0.000    -.0285724    -.014766
 kihasznaltsag |   .0178317   .0049954     3.57   0.001     .0076149    .0280484
kataszteripont |   .0053164   .0017329     3.07   0.005     .0017723    .0088605
        _cons |   7.775135   .6817945    11.40   0.000     6.380708    9.169561
------------------------------------------------------------------------------

. estimates store EAK

.
. reg kkit maxhozam kihasznaltsag kataszteripont

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  3,    29) =   25.81
       Model |   31127.722     3  10375.9073           Prob > F      =  0.0000
    Residual |  11657.6412    29  401.987627           R-squared     =  0.7275
-------------+------------------------------           Adj R-squared =  0.6993
       Total |  42785.3632    32   1337.0426           Root MSE      =   20.05

------------------------------------------------------------------------------
         kkit |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     maxhozam |  -1.175122   .2194706    -5.35   0.000     -1.62399   -.7262545
 kihasznaltsag |    .924396   .3248166     2.85   0.008     .2600714    1.588721
kataszteripont |   .3378422    .112677     3.00   0.006     .1073919    .5682926
```

```
         _cons |   126.3618    44.3324     2.85   0.008     35.69183    217.0317
------------------------------------------------------------------------------

. estimates store ERK

.
. reg qk50 maxhozam kihasznaltsag kataszteripont

      Source |       SS       df       MS              Number of obs =      33
-------------+------------------------------           F(  3,    29) =   27.50
       Model |  30714.1581     3  10238.0527           Prob > F      =  0.0000
    Residual |  10796.6661    29  372.298831           R-squared     =  0.7399
-------------+------------------------------           Adj R-squared =  0.7130
       Total |  41510.8242    32  1297.21326           Root MSE      =  19.295

------------------------------------------------------------------------------
          qk50 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
      maxhozam |  -1.421738   .2112106    -6.73   0.000    -1.853712   -.9897638
 kihasznaltsag |   .6708873   .3125919     2.15   0.040      .031565     1.31021
kataszteripont |   .2042787   .1084363     1.88   0.070    -.0174985    .4260559
         _cons |    193.708   42.66392     4.54   0.000     106.4504    280.9655
------------------------------------------------------------------------------

. estimates store EQK.
```