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Essays on Time Varying Parameter Models

Ph.D. dissertation

Supervisor:

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Senior Researcher

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Department of Mathematical Economics and Economic Analysis

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Contents

Summary

The thesis consists of four independent papers which are connected through the topic of time varying parameter models. The first chapter reviews the time-varying regression model and presents its solution methods, while the next three chapters carry out applied research using time varying parameter models in the field of macroeconomics. The second and third chapters are also available as separate English language articles.

Chapter I is an edited version of *Varga* [2011]. It is a comprehensive introduction into the estimation methods of time varying coefficient linear models. At first the state space representation and the popular Kalman filter are reviewed, along with the very similar (and much lesser known) Flexible Least Squares. The recently uncovered subtle differences between the two models are discussed. Then we show the alternative Markov Switching method which can also be used for estimation of TVC models. The qualities of the two model families are illustrated with simulation experiments.

Chapter II is based on the article of *Darvas* and *Varga* [2014]. The chapter studies inflation persistence with time-varying coefficient autoregressions for twelve Central European countries, in comparison with the United States and the euro area. Inflation persistence tends to be higher in times of high inflation. Since the oil price shocks, inflation persistence has declined both in the US and the euro-area. In most central and eastern European countries, for which our study covers 1993-2012, inflation persistence has also declined, with the main exceptions of the Czech Republic, Slovakia and Slovenia, where persistence seems to be rather stable. These findings have implications for the conduct of monetary policy and for a possible membership in the euro area. We also conclude that the OLS estimate of an autoregression is likely upward biased relative to the time-average of time-varying parameters, when the parameters change.

Chapter III is an edited and translated version of *Varga* [2013]. The paper estimates Phillips curve relationships for the data of four Central European countries, the Czech Republic, Hungary, Poland and Slovakia, using a sample period from the mid-1990s till 2012. For the estimation *Gordon*'s [1997, 1998] triangle model is used with the Kalman filter, where the time-varying NAIRU is described as a latent variable following a random walk, and its

deviation from the actual unemployment rate – the unemployment gap – affects inflation, among other factors. The results concerning the inflation-unemployment tradeoff are in line with the literature, however, the coefficient for Poland and Slovakia are insignificant. The natural rate of unemployment for the Czech Republic has a decreasing tendency while the one for Hungary has a strong increasing tendency throughout the entire sample. The inclusion of inflation expectations is found to be statistically significant, albeit it significantly reduces the size and significance of the unemployment gap coefficient.

Chapter IV, based on *Varga* [2014] explores the time varying relationship of investment and saving as a measure of financial openness. The since well-known paper by *Feldstein* and *Horioka* [1980] identified a country's financial openness as a cross-sectional relationship between the domestic investment rate and the savings rate. This chapter estimates various time varying measures of the investment-savings relationship with the use of the Kalman filter on a panel database consisting of 126 countries and 51 years. After examining whether the two time series are cointegrated we build a new model version to avoid spurious regression. The estimation results are the sequences of the savings-retention coefficient country by country which are analyzed on a world and continent level, and compared to two other measures of financial openness. Our results are in line with the view that, on average, the degree of financial openness has increased dramatically in the past 50 years; furthermore, significant co-movement with other financial openness measures is also found.

Last we sum up the novelties in our work. The models in the first chapter are standard, however, the simulation is fairly unique in the way that it not only compares Kalman-filtering and Markov-switching models, but also includes Flexible Least Squares. The second and third chapters estimate already existing models on Central- and Eastern European (CEE) countries' data which – to our knowledge – has never been done before. The fourth chapter synthesizes and extends the estimation of the time varying savings-retention coefficient to a worldwide database, while also introducing a modified model, and comparing the estimated results to other existing financial openness measures.

I. An Introduction to Time Varying Parameter Models: a Simulation Study

I.1 Motivation

The beginning chapter serves two purposes: to introduce the mechanics of time-varying parameter estimations, and to illustrate how they work in real life through simulations. As for the first, the Hungarian economic literature lacked an introductory methodological paper on time varying parameter models before, and our article fills that gap. Furthermore, the paper seems to be a logical opening of a dissertation dealing with such models. As for the second, besides illustrational purposes, the subtle difference between the Kalman-filter and the not so well known Flexible Least Squares might be worth investigating. This part also bears a value added to the literature.

I.2 Applied Methods

Granger [2008] shows that any nonlinear time series model can be approximated using a time varying parameter linear model, and thus argues that time varying parameter models could be the next big thing in economic research because of their easier interpretability and ability to make multi step-ahead forecasts. The departing point for the methods reviewed here is the standard time varying coefficient regression:

$$y_t = \beta_t' x_t + \varepsilon_t,$$

where the coefficient vector β_t is allowed to vary over time. To build a state-space system out of this the most straightforward step is to regard the above as a signal equation while adding a state equation which makes an assumption about the dynamics of the latent variable β_t:

$$\beta_t = \beta_{t-1} + \omega_t.$$

In this case β_t follows a random walk with the innovations ω_t. The famous Kalman filter invented by *Kalman* [1960] searches for a serial updating mechanism of β_t which satisfies two requisites: (*i*) the estimate is linear in y_t, and (*ii*) the estimate minimizes the sum of squared signal residuals over the entire sample. The filter assumes all parameters are known but after running it also produces the log-likelihood value which can be later maximized to estimate any system parameters.

The Flexible Least Squares method invented by *Kalaba* and *Tesfatsion* [1988, 1989, 1990a] produces just the same as the Kalman filter – as proved by *Montana* et al [2009], but relies on merely different principles. In the sense of not making any probabilistic assumptions it does not introduce any random quantities in the state and signal equations above, but simply aims for minimizing a pre-specified cost function:

$$C(\beta,\mu)=\sum_{t=1}^{T}(y_t-\beta_t'x_t)^2+\mu\sum_{t=1}^{T-1}(\beta_{t+1}-\beta_t)'(\beta_{t+1}-\beta_t).$$

Here we see a weighted sum of the two types of sum of squared errors associated with the two equations above. The first is a measurement error while the second is a dynamic error associated with the latent variable β_t. The weight parameter $\mu > 0$ is arbitrary and there exists a unique solution for every single μ value. *Kalaba* and *Tesfatsion* argue that the method is a multi-criteria optimization approach to the state space filtering problem and that the solution depends on the specific need of the researcher: by setting different μ values one can arrive to a set of solutions which all lie on a Pareto-type two-dimensional residual efficiency frontier, defined by the measurement and dynamic sum of squared errors.

Montana, *Triantafyllopoulos* and *Tsagaris* [2009] put an end to the long-standing debate whether the FLS actually differs from the Kalman filter. They showed that computationally they are clearly the same, and the Kalman filter algorithm also minimizes the quantity

$$\sum_{t=1}^{T}(y_t-\beta_t'x_t)^2+\sum_{t=1}^{T-1}(\beta_{t+1}-\beta_t)'V_\omega^{-1}(\beta_{t+1}-\beta_t)$$

where V_ω is the covariance matrix of the state innovations. This corresponds to the above incompatibility cost of *Kalaba* and *Tesfatsion* if we introduce the restriction for the state covariance matrix

$$V_\omega=\mu^{-1}I_p.$$

This shows the real difference between the two methods: the FLS restricts the variance structure of the latent vector, but both methods work in the absence of any probabilistic assumptions.

If we restrict the state variable to a finite number of possible values – or regimes, we can retain the signal equation and replace the state equation with the assumption that the state variable follows a Markov-chain. This leads us to the well-known Markov switching model which can be solved in a way which is quite analogous to Kalman-filtering. The solution of the Markov switching model is also detailed in the chapter.

I.3 Results

The simulation part of the chapter aims to compare the Kalman filter, the FLS and the Markov switching model in a Monte Carlo simulation environment. All three models are employed in a filter and also in a smoother form, and we look at the FLS with three different weight parameters: the optimal, a bigger, and a smaller value. In the base scenario we made five assumptions on the true β_t coefficient vector, we now review the results grouped by these.

- When β_t is constant through the entire sample, all methods provide good guesses but the Markov estimation has a bigger standard deviation. This is due to the inherent misspecification error in the Markov model.
- When the coefficient has a discrete break in the sample interval, the Markov model – which is truly fitted to this case – outperforms, but the continuous models are also usable, however, these tend to smoothen out the coefficient break.
- In the case of the coefficient having a linear trend, and in the case of the coefficient having a sinusoidal trend, the Kalman filter and FLS are better, while the Markov models tend to produce step-like estimations. These two cases are quite similar to each other as both mean continuous changes in the coefficient.
- When β_t follows a random walk, the behavior of the Markov model depends largely on the specific trajectory of the coefficient, but this case is also much more fitted for a continuous model.

In the next part of the simulation we introduce four alternative scenarios, and we run all five simulations based on the coefficient vector in each one of them.

- We introduce heteroskedasticity in the model. The Markov model – depending heavily on normality assumptions – gets worse in all simulations; the FLS selectively worsens, while the Kalman-filter is remarkably consistent.
- The distribution of the error term is changed from normal. Both continuous models perform just as good as in the baseline, the Markov model gets beaten when faced a strongly leptokurtic distribution.
- A step-function disturbance appears. The Markov model doesn't really change because of the discrete regime-estimations, but the two continuous models do. Again, the FLS results are a lot more erratic while the Kalman-filter worsens evenly across simulations.

Generally we found that the smoother versions outperform the filters at all circumstances – the filters tend to lag behind the true coefficient sequence. We also found that the FLS is bounded with its variance restriction and that the Kalman filter tends to outperform it even when the FLS uses the optimal weight parameter. On the other hand though, the numeric optimization involved when using the Kalman-filter can also be an obstacle, and the easy-to-handle one parameter solution of the FLS can be attractive. All in all, both methods have their own advantages and favorable estimation conditions. Our results add new insights to the FLS simulation literature made up by *Kladroba* (2005) and *Darvas* and *Varga* [2012].

II. Inflation Persistence in Central and Eastern European Countries

II.1 Motivation

The adjustment of inflation towards its long-run level after a shock can be characterized by the speed with which it converges back to its mean. The greater this speed, the less complicated the central bank's task of maintaining price stability. Inflation persistence (IP) is a measure of this convergence speed, based on different kinds of properties of the impulse response function within the model built to describe inflation. Although the analysis of inflation persistence in the euro area and the USA has received much attention, there has been very limited research regarding the central and eastern European (CEE) countries. Understanding inflation persistence in CEE countries is not just crucial for the central banks of these countries for the conduct of monetary policy, but it also has implications for their future membership of the euro area. Similar persistence to that of the euro area will be essential for the optimality of the common monetary policy.

Time-varying coefficient analysis of inflation persistence in CEE countries seems inevitable, because these countries went through substantial structural changes when transformed their economies and institutions from socialist to market systems. The transformation process was a gradual one and the economies of these countries probably still changing in a faster pace than mature economies. These arguments imply that it is rather difficult to set a date from which constancy of the parameters could be assumed on safe grounds.

II.2 Applied Methods

We investigate the quarterly inflation time series of the US and the euro area, and twelve Central and Eastern European Countries (CEEC's): Albania, Bulgaria, Czech Republic, Estonia, Croatia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The effective sample period for the US is 1959Q1-2012Q4, for the euro area 1972Q1-2012Q4, and for the CEEC's 1995Q1-2012Q4.

Before estimating any time varying model we employ several formal tests to check whether there has been a significant change in the persistence of our inflation series. We use the tests by *Kim* [2000] and *Busetti-Taylor* [2004], both modified by *Harvey*, *Leybourne* and *Taylor* [2006].

There are different measures of inflation persistence of which the most common is the parameter of a first-order autoregression, or the sum of the autoregressive parameters of a higher order autoregression. We also adopt a higher order autoregression and allow the parameters to change in time:

$$y_t = \rho_{0,t} + \rho_{1,t} y_{t-1} + \cdots + \rho_{p,t} y_{t-p} + u_t,$$

where y_t is an observed variable, $\rho_{i,t}$ denote the parameters which can change in time, and u_t is the error term. Since we use quarterly data, we allow for at most six lags in the autoregression and use the Box-Pierce and Ljung-Box statistics to determine the optimal length. Our measure of inflation persistence at time t is the sum of the autoregressive parameters:

$$IP_t = \sum_{i=1}^{p} \rho_{i,t}.$$

For the estimation we use both the FLS with a μ weight parameter of 100, and Kalman-filtering via Maximum Likelihood. For both methods we report the filtered estimates (which, for time t, are based on data up to time t, though the estimation of parameters uses the full sample of data) and the smoothed values (which, for time t, are based on data up to the end of the sample). For comparison, we also show the OLS estimate both for the full sample (which corresponds to the smoothed estimate of FLS and Kalman-filter), and also for recursive samples (which corresponds to the filtered estimates of FLS and Kalman-filter). Naturally, at the last data point the recursive OLS equals the full sample OLS, and the filtered values of the FLS and Kalman-filter correspond to the smoothed values of the FLS and Kalman-filter, respectively. The findings of *Darvas* and *Varga* [2012] suggest that the FLS with a weight parameter setting of 100 works reasonably well, and that we should prefer the smoothed values relative to the filtered values.

II.3 Results

After applying the formal persistence change tests we cannot reject the null hypothesis of constant persistence stationarity against the alternative of a change from stationarity to nonstationarity, but we reject, for most time series, the null hypothesis against the alternative of a change from nonstationarity to stationarity, though for Latvia and Slovakia the rejection can be made at 10 per cent significance level only. We therefore conclude that there were statistically significant structural breaks in the persistence of the inflation time-series we analyse.

Since the oil shock, inflation persistence declined to historically low levels in the US and euro area, yet it remained higher in the euro area (where persistence was practically constant since the creation of the euro) than in the US. In most central and eastern European countries inflation persistence has declined since 1995, with the main exceptions of the Czech Republic, Slovakia and Slovenia, for which the Kalman-smoother suggested constant persistence, and the FLS-smoother a minor fall in persistence. For most CEE countries, inflation persistence became similar to the persistence in the euro area, which means reasonably low, far from full persistence.

It seems evident for all countries that the OLS persistence estimate is much larger than the time-average of the time-varying persistence estimations. We therefore perform a one-sided *t*-test to assess the difference between the OLS estimate and the time-average of the time-varying ones. The results clearly show that the OLS estimates are significantly higher than the average of the time-varying ones, the null hypothesis of equality cannot be accepted for any of the countries. So we conclude that the OLS estimate of the parameters of an autoregression is likely *upward* biased relative to the time-average of time-varying parameters, when parameters change in time. This finding complement the literature, which concluded that the OLS estimate of the autoregressive coefficient (or the dominant autoregressive root) is *downward* biased when parameters are fixed.

III. Time Varying NAIRU Estimates in Central Europe

III.1 Motivation

The US economy in the mind-90's, also known as the Goldilocks, was characterized by falling inflation and low unemployment, which contradicts the theory of a constant natural rate of unemployment, or NAIRU. Therefore it was the inspiration for *Gordon* [1998] to come up with his time varying NAIRU model which became a seminal work and has been adopted many times. However, because of estimation difficulties, small sample issues and other problems, the literature tends to restrict the NAIRU dynamics to follow a common trend with the unemployment rate.

The Central European transition countries faced an analogous situation to Goldilocks in the late 90's when both unemployment and inflation decreased from their extreme levels following the transition shock. This observation, added to the fact that we are observing a massive structural transition in these countries, encourages us to look for time varying NAIRU sequences. We argue that despite some difficulties, *Gordon*'s original triangle model should be used, which lets the estimated natural rate series free and be influenced only by the observations.

III.2 Applied Methods

Gordon's [1997, 1998] triangle model can be thought of as the bivariate representation of the well-known backward looking Phillips curve: while unemployment itself follows a random walk, it forms a short run relationship with inflation through a demand pressure term in inflation dynamics – specifically, the deviation of unemployment from a time varying NAIRU. Thus, in this setting, NAIRU accomplishes just what it's defined for: a level of unemployment which does not carry any inflationary pressures. Inflation, besides depending on this deviation term, is also determined by its own inertia and some exogenous supply shocks. Also, by introducing forward looking dynamics as done by *Driver*, *Greenslade* and *Pierse* [2006], the model can be augmented to fit the New Keynesian Phillips Curve (NKPC) concept where price stickiness causes inflation expectations to play an important role in price determination. Our state space model has the form

$$U_t^* = U_{t-1}^* + \eta_t$$
$$\pi_t = \alpha(U_t - U_t^*) + \beta(L)\pi_{t-1} + \gamma\pi_{t+4}^e + \delta(L)z_t + \varepsilon_t$$
$$\eta_t \sim N(0, \sigma_\eta^2), \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \text{cov}(\eta_t, \varepsilon_t) = 0$$

where π_t is annual price inflation (we use quarterly data and therefore define inflation as the percent change compared to the same quarter of the last year); π_{t+4}^e– is the expected inflation one year ahead; U_t is unemployment and U_t^* is the time varying NAIRU; $\alpha, \beta(L), \gamma$ and $\delta(L)$ are coefficients and lag polynomials of coefficients, η_t and ε_t are error terms associated with the state equation (1) and signal equation (2), respectively. Finally, z_t represents exogenous supply side shocks in real terms, namely annual real oil price inflation and annual real import price inflation. We use uniformly 5 (quarterly) lags of inflation and 1-1 lag of oil and import price shocks for all countries studied.

In the long run there is assumed to be no tradeoff between inflation and real activity, the Phillips curve is vertical. In order to realize this long-run NAIRU neutrality in the sample, two restrictions must be placed: first, the sum of inflation coefficients – $\beta(L)$ and, if present, γ – must equal to unity; and second, the supply side shock series must be normalized so that their sum over the sample is zero.

The model is estimated by using the Kalman filter via maximum likelihood; this allows us to simultaneously estimate both the NAIRU sequence (with the Kalman filter and smoother running inside the likelihood function) and all the unknown coefficients (by maximizing the likelihood function). The method has one significant drawback: there are too many degrees of freedom to estimate both the σ_ε^2 variance of the signal equation and the σ_η^2 variance of the state equation, one of them must be arbitrarily set. Our strategy is that for each country, after careful analysis of the measured volatility of unemployment series, we use three variance presets for σ_η^2 which probably cover a reasonable range and show how the estimated NAIRU changes along with these variance presets. As a general rule we only regard the estimated NAIRU sequences where the unemployment gap coefficient proves significant in the model, otherwise the estimated NAIRU sequence is not meaningful.

III.3 Results

For a comparison, we show the results of *Driver et al* [2006] concerning the unemployment gap coefficient: for the US, their values were around -0.40, and around -0.25 when accounting for inflation expectations. For the UK, their estimates were -0.85 and -0.80, respectively. *Turner et al* [2001] who estimated nearly the same equation (without expectations included) for 21 developed countries, reported unemployment gap coefficients between -0.13 and -2.66.

For the Czech Republic, the models omitting inflation expectations show a highly significant unemployment gap coefficient around -0.30, and the estimated NAIRU has a clear decreasing tendency from 7-8% to 5.5-6.5%. When we include the expectations term (which is highly significant), the estimated coefficient of the unemployment gap term is still significant but this time lower: -0.17 to -0.19. The NAIRU sequences show a somewhat different picture, peaking in the period 2006-2008 but decreasing since then. Overall, the Czech Republic's results are remarkably in line with those of the US or any developed country, and the NAIRU sequence shows a steady decline throughout much of the sample.

For Hungary, the estimated unemployment gap coefficient is still significant, albeit much lower: -0.10 to -0.15. The estimated NAIRU sequence shows a huge increase which contradicts the results of *Guichard–Rusticelli* [2011], who estimate the NAIRU for Hungary using a more restricted model and get a result sequence closely tracking the unemployment rate itself.

For both Poland and Slovakia our estimated unemployment gap terms are well in line with Guichard and Rusticelli [2011], although insignificant. Therefore we don't get any inference from the NAIRU sequences.

For all samples we found that both backward and forward looking inflation elements are highly significant, even in the presence of one another. However, when controlling for inflation expectation series, the unemployment rate gap coefficient is a lot closer to zero and loses from its significance.

IV. A Time Varying Parameter Estimation of the Investment-Savings Relationship

IV.1 Motivation

The since well-known Feldstein-Horioka paper identified a country's financial openness as a cross-sectional relationship between the domestic investment rate and the savings rate. In the last decade there has been a surge of literature estimating various time varying measures of this investment-savings relationship but the results are scattered and only cover a handful of countries. We estimate the time varying savings-retention coefficient with the use of the Kalman filter on a panel database consisting of 126 countries and 51 years and build a new model version to avoid spurious regression, giving our results formal statistical justification.

The estimation results are the sequences of the savings-retention coefficient country by country which we analyze on a world and continent level, and compare to two other measures of financial openness.

IV.2 Applied Methods

Looking at the original equation of *Feldstein* and *Horioka* [1980] which regresses the domestic investments-to-GDP ratio on the domestic savings-to-GDP ratio on a cross-sectional sample, we first mention that there is a serious flaw in regarding the estimated savings-retention coefficient in itself. The postulated perfect lack of mobility arises not when the coefficient equals – or is close to – unity, but when it is close to unity *and* the estimated standard deviation of this coefficient is small (or the R-squared is big).

We build three time-varying coefficient models based on the original Feldstein-Horioka equation. The first is the time varying cointegration equation model (TVCE) which is simply a regression in time varying form:

$$\beta_{0,t} = \beta_{0,t-1} + \omega_{0,t}$$
$$\beta_{1,t} = \beta_{1,t-1} + \omega_{1,t}$$

$$i_t = \beta_{0,t} + \beta_{1,t} s_t + \varepsilon_t$$

Here i_t represents the country's investment-to-GDP ratio and s_t the savings-to-GDP ratio. The first set of equations adds up to form the state equation and the last one makes the signal equation. This system is highly exposed to spurious regression because the investment and savings ratios are likely to be integrated processes. To avoid this, we also include lags in the signal equation:

$$i_t = \beta_{0,t} + \beta_{1,t} s_t + \beta_{2,t} i_{t-1} + \beta_{3,t} s_{t-1} + \varepsilon_t,$$

thus building a new model version, dubbed the TVCEL model (TVCE with Lags). The problem now is that we increased the number of latent variables to be estimated to four, this could greatly increase our sampling error. In these two models we regard the $\beta_{1,t}$ coefficient as the measure of financial openness.

Another option to avoid spurious regression would be to look at a time-constant cointegration and make the error correction equations time varying (TVECT setup). This is rarely done in the Feldstein-Horioka literature.

$$i_t = \beta_0 + \beta_1 s_t + u_t$$

$$\alpha_{i,t} = \alpha_{i,t-1} + \omega_{i,t}$$
$$\alpha_{s,t} = \alpha_{s,t-1} + \omega_{s,t}$$

$$\Delta i_t = \sum_{l=1}^{k} \phi_{\mathrm{i,i}}^{(\mathrm{l})} \Delta i_{t-l} + \sum_{l=1}^{k} \phi_{\mathrm{i,s}}^{(\mathrm{l})} \Delta s_{t-l} + \alpha_{i,t} u_{t-1} + \varepsilon_{i,t}$$
$$\Delta s_t = \sum_{l=1}^{k} \phi_{\mathrm{s,i}}^{(\mathrm{l})} \Delta i_{t-l} + \sum_{l=1}^{k} \phi_{\mathrm{s,s}}^{(\mathrm{l})} \Delta s_{t-l} + \alpha_{s,t} u_{t-1} + \varepsilon_{s,t}$$

Here, the first equation shows a time-constant cointegrating regression which is estimated separately (via Johansen's method). Then the $\alpha_{i,t}$ and $\alpha_{s,t}$ adjustment coefficients are modeled as the latent variables and the lower two error correction equations are the signal equations. Here we regard $\alpha_{i,t}$ as the time varying measure of financial openness.

All three models are estimated via Kalman filter and maximum likelihood on a 51 year long (1960-2010) sample of 126 countries. The dataset is not balanced; the longest balanced subsample is 16 years, from 1990 to 2005.

Before looking at the estimates we carry out a multitude of cointegration tests, both single (one test outcome for each pair of investment-saving time series) and grouped (one test outcome for all pairs). We also perform *Hansen*'s [1992] parameter instability test where the null hypothesis is cointegration and the alternative is not only time varying cointegration but any case where the data do not support the assumption of a constant cointegration.

When examining the estimated coefficient sequences, we produce world and continent averages to put the results in a well-readable form. We consider two options to calculate averages: an unweighted and a GDP-weighted version.

To compare our by-country results with other financial openness measures found in the literature, we perform panel regressions on the difference of our savings-retention coefficient measure and (*i*) the difference of the KAOPEN de jure measure by *Chinn* and *Ito* [2008], and (*ii*) the log-difference of the IFIGDP de facto measure by *Lane* and *Milesi-Ferretti* [2007].

IV.3 Results

While the single cointegration tests reject cointegration for the majority of countries, all the group tests strongly signal cointegration. *Hansen*'s (single) parameter instability tests reject constant cointegration only in about 20% of all countries.

Looking at the world-averaged results, both the unweighted TVCE and TVCEL savings-retention coefficient estimators show a firm decrease from about 0.5 to 0.35, even when looking only at the balanced subsample. The results of the two models are quite similar which shows that the cointegration is mostly present, as suggested by the group tests. The average financial openness accelerates in the last two decades, which is in line with, and extends, the works of *Taylor* [1996] and *Jansen* [1996].

The GDP-weighted savings-retention coefficients don't show a significant decrease which can signal that the coefficient in big and/or developed countries didn't change much during the sample period. Also the values of the savings-retention coefficient are much higher here, about 0.8 to 1.0, this possibly shows the capital mobility advantage of small countries which has already been discussed by the literature.

The TVECT model does not show any meaningful variation. This may signal that the time constant cointegration assumption is too strong to show any change in the adjustment coefficients.

The panel regressions with other financial openness measures show that our results correlate significantly with the IFIGDP measure of *Lane* and *Milesi-Ferretti* [2007]. This relationship is even more pronounced when instead of simply using the savings-retention coefficient we use its *t*-statistic, based on the reasoning described in the first paragraph of (IV.2).

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