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CORVINUS UNIVERSITY OF BUDAPEST

THE RELATIONSHIP BETWEEN ANALYST FORECASTS, INVESTMENT FUND FLOWS AND MARKET RETURNS

Ph.D. Dissertation

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A study of Emerging European Equity Markets

(Ph.D. dissertation)

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1. Introduction

„Individual expectations about future aggregate outcomes [are] the key feature that distinguishes social sciences and economics from the natural sciences." (Hommes, 2010, p. 2.) Economics engages with individuals as actors, and with their interactions that weave into a system. This system is limited by the ambiguity of investor expectations: what the average opinion of investors is about average opinion. Classical economics dismisses the speculation on expectations by assuming that investment decision-making is rational. Thus, theories on the Efficient Market Hypothesis and the subsequent emergence of the Capital Asset Pricing Model gained popularity. The world as we know it proved that these theories are unrealistic, and behavioural finance emerged as an alternative solution focusing on investors with bounded rationality. In order to relieve the restrictive assumptions of the CAPM, such as the assumption of homogeneous expectations: heterogeneous agent models of investors emerged. This gave rise to my research question to examine how differences of opinion of individual investors may be captured. Since, the opinion of investors cannot be observed directly, I collected sell-side analyst forecasts, a regularly published set of data and I assumed it to be a proxy of investors' expectations on future market returns.

If markets were as efficient as the strong form of the Efficient Market Hypothesis suggests, then prices would already incorporate all available information. Thus, examining analyst opinion data would be redundant to understand equity market returns. However, my experience as a sell-side equity analyst gives me an oversight of the microstructure of the equity markets. When new information emerges, investors adjust their trades instantaneously. As a result, stock prices quickly reflect the new information. Analysts, on the other hand, would revise their fundamental models and adapt their research ideas with a lag (perhaps in a few days time). It is their research product that reflects a more thorough interpretation of the new information. The extent to which prices would fully-reflect the processed new information depends on the work of analysts alongside investors. The equity research

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industry inspired scientific research to examine the implications of the aggregate opinion of sell-side analysts. Does the dispersion of analyst opinion tell us anything about market returns?

Another separate line of research seeks to understand market returns focused on the relationship between investment funds' aggregate net flows and equity market returns. The research on this topic mostly covers developed markets. Intuitively, fund flows ought to drive returns and vice versa, returns ought to attract flows into the investment funds.

The unconnected research papers motivated me to examine how equity markets work with a view of the market microstructure, taking into account that analyst opinion and fund flows are not independent from one another. Analysts serve their investor clients, who make investment decisions, which are reflected in fund flow data. I became curious to understand how information passes from analysts to their institutional investor clients (fund managers), and onto the individual investors (e.g. retail clients), who induce the fund flows. Eventually, flows into and out of investment funds will lead to trading, that registers different opinions into asset prices. Therefore, examining the relationship between the three elements together, namely analyst forecasts, investment fund flows and asset returns, is justified. It is also a novice approach that I hope would help me find new results to better explain the efficiency of equity markets.

Another interesting aspect of my research is that I examine Emerging European equity markets, a segment that was left untouched by the international literature on both analyst forecasts and fund flows. Furthermore, my empirical research covers a period of 12 years (from Autumn, 2000 – Spring, 2012) which is considered to extend over a complete economic cycle, with sub-periods spanning an economic boom in the early-mid years of the past decade, and the years of the recent financial crisis. It is interesting to see whether results differ in a pre-crisis from a post-crisis period.

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This dissertation will first introduce the history of equity market returns. Classical economic theory that presents the Efficient Market Hypothesis, its proponents and opponents is discussed in the first chapter. Then, in chapter 2, I introduce the market microstructure: how markets work. Investors, analysts and brokerage firms are interrelated, and the professional relationship reveals that analysts on the sell-side give their opinion in the form of investment recommendations and target prices on assets they cover. Inventors are the recipients of the research, and also, they are the investment decision-makers. In chapter 3, I present the measurement of analyst opinion, and the methodology of aggregating analyst opinion to cover countries (rather than single stocks) to make them comparable with country-related fund flow data. In chapter 4, I present the literature on the relationship between analyst forecasts and returns. The papers are presented chronologically. This is followed by chapter 5, where I present the literature on the relationship between investment fund flows and market returns. This area of research is covered only by a handful of papers. In chapter 6, I outline my empirical work, introducing the datasets at hand, my hypotheses, the methodology and the results of my empirical examinations.

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2. Classical Economics

Classical economics asserts that the role of capital markets is to efficiently allocate resources between savers and borrowers, investors and investment projects. The emphasis here lies on efficiency; which is considered to comprise three interdependent components. The first is *informational efficiency*, which is related to the dissemination of information related to making investment decisions. The second is transactional or *operational efficiency* that deals with costs associated with allocating resources. If a capital market exhibits operational efficiency that means that the costs of transferring funds are at a minimum. The third part is termed *allocation efficiency*. This concerns the successful allocation of funds to profitable investment projects; all projects with positive net present value will find the required funds.

These three measures of efficiency are inter-related, with allocation efficiency contingent on informational and transactional efficiency. (Hendry and King, 2004) This is best demonstrated by an example from (*ibid.* p. 7.) Poor disclosure of information coupled with higher uncertainty created low informational efficiency. This may lead investors to increase risk premia embedded in their required rate of return, which raises the cost of capital for investment projects. The new rise in costs will result in some investment projects – profitable under the information efficient environment – being deemed unprofitable and therefore go unfunded. This affects the flow of funds within the economy, and creates an inefficient allocation of resources across projects in comparison to the status quo. In turn, market-makers and other financial intermediaries who think they are trading against better-informed investors may have a lower risk appetite. This may lead to a dry-up in liquidity resulting from higher bid-ask spreads, thus induce low operational efficiency.

This shows that the three aspects of efficiency are related and are linked via hierarchy. The level of informational and operational efficiency helps determine the degree of allocation efficiency. (Bauer, 2012) Inefficiency in one area would contribute to inefficiency in the other two aspects. In such an environment, society incurs dead-weight costs caused by the below optimum economic growth. This dissertation will focus on the first level of efficiency in the hierarchy, which is informational efficiency.

Classical theories on financial markets were formulated in the first half of the past century with the emergence of the efficient market hypothesis (EMH) in 1954 by a number of economists, but mostly the name of Fama became associated with it. The roots of EMH can be traced back to the theory of random walk introduced in earlier studies such as Bachelier's thesis in 1900 (Davis and Etheridge, 2006), Working (1934) and Cowles and Jones (1937). However, the theory did not enjoy public awareness before the publishing of Malkiel's famous book entitled "A Random Walk Down Wall Street" in 1973. According to Malkiel (1973) a random walk is a process that assumes that stock prices evolve randomly. This means that upward and downward movements in stock prices occur with equal probabilities making price shifts unpredictable. Random walk has the following two properties: successive price changes are independent and identically distributed. Formally,

$$f\left(r_{j,t+1} \middle| \Phi_t\right) = f\left(r_{j,t+1}\right)$$

1. Equation

(Fama, 1970, p. 386.), where $r_{j,t+1}$ is the return on stock *j*, Φ_t represents the set of information available at time t, and f is the probability distribution function of the returns.

The efficient market hypothesis was further popularised by Fama, who alongside with Paul Samuelson rediscovered Bachelier's Theory of Speculation in the 1960s. This inspired them to put a mathematical framework into use with stochastic calculus to describe movements in financial markets. (Davis and Etheridge, 2006)

Fama later defined the efficient market hypothesis (EMH), in his 1970 paper that received high citation later on. According to him, the theory says that an efficient

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market is one “in which prices always fully reflect available information (Fama, 1970, p. 383.) and that “adjusts rapidly to new information.” (Fama et al., 1969, p. 1.) In his wording, “fully reflect” insinuates that all existent information is priced-in, and no extra-profits can be made by fundamental or technical analysis. As a consequence, prices will always reflect the fundamentals; any possible excess returns earned by an investor results purely by chance. Then, how is the fact consistent with this theory, that some portfolio managers constantly beat the market? The answer to this puzzle is that with hundreds of thousand investors, even a normal distribution of asset returns would allow for a few “star investors” to exist.

In this sense a portfolio composed of arbitrary stock weights α_i yields zero expected excess return, formally (Fama, 1970, p. 385.):

$$E\left(V_{t+1} \middle| \Phi_t\right) = \sum_{j=1}^{n} \alpha_j(\Phi_t) E\left(\tilde{z}_{j,t+1} \middle| \Phi_t\right) = 0$$

2. Equation

where V_{t+1} is the total excess value generated at time $t+1$, $\tilde{z}_{j,t+1}$ is the excess return on stock j, and Φ_t denotes the information set at time t. If excess returns equal zero, investors may increase their returns at the expense of assuming higher risk, as per the classical CAPM model.

Fama (1970) defined three forms of market efficiency: the weak, the semi-strong and the strong form of market efficiency, that all relate to the subset of information priced-in into stock prices.

In its weakest form, the efficient market hypothesis assumes that all historical share prices are incorporated into asset prices. Therefore, no excess returns may be earned using investment strategies based on past returns. From this stems that technical analysis – a study of chart formations of past returns – is useless in predicting future returns. Since the market already knows the past, the current information remains the unknown. For this reason, fundamental analysis gains attention as it becomes

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rewarding for those keen investors who do their homework on companies' financial statements.

Tests for the weak form of efficiency engage in historical data analysis using statistical and econometric methods. Analyses include testing the effect of market value, P/E, DIV/P, and book-equity-to-market-equity on historical returns. Also, technical analysis is prevalent in testing for the weak form of efficiency.

The levels of efficiency gradually increase their restrictions. It is therefore natural for the next level to include the previously stated assumptions. In addition to historical data, the semi-strong form of efficiency incorporates publicly available new information rapidly into pricing; this insinuates that fundamental analysis will not earn investors excess returns.

Testing for the semi-strong form of efficiency is carried out using event studies. The emergence of new information usually takes the form of quarterly or annual reports or events such as mergers, acquisitions, purchase of treasury shares, new share issuances or stock splits. The emergence of such news should induce markets to adapt quickly. Market efficiency may be captured by measuring the speed of adaptation to new information.

The highest level of efficiency is the strong form. Under this form, prices incorporate all existing information, both public and private. Under such efficiency level, none earn extra profits. In reality, however, laws prohibit trading using insider information. Testing the strong form of market efficiency is, in essence, a test for the existence of insider trading, as examined by Damodaran and Liu (1993) In such a test, the goal is to reveal the investment activity of interest groups with monopoly over key decisions in the companies, or with knowledge of market moving information prior to their publication. The existence of trading based on insider knowledge may be observed in price adjustments taking place before significant (i.e. price moving) announcements are made public.

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2.1. Empirical Findings Supporting EMH

According to Fama (1970) markets are efficient if there are no transaction costs and if information is freely available to investors. Moreover, all investors draw the same inferences about the current information available, which means they have homogeneous expectations. Fama (1991) argues that although these conditions are not likely to be met in the real world, markets are still efficient, and refers to a weaker definition for market efficiency to tackle the first two conditions based on Jensen (1978) "Prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed marginal costs." (Jensen, 1978, p. 1575.)

The third condition may also not pose as a problem. Despite the disagreement amongst investors, should this disagreement be "random" then no group of investors can consistently make better evaluations, and thus the notion of market efficiency is not violated. This insinuates that not all investors are necessarily rational, but it is sufficient for the nature of irrationality to be random, and that guarantees that investors as a community will behave rationally.

Fama (1970) established the concept of the efficient markets and tested this hypothesis empirically concluding that markets satisfy the semi-strong form of efficiency, with limited evidence refuting the strong form of market efficiency. These results were previously bolstered by Jensen (1968). Jensen's empirical study of the performance of 115 U.S. mutual funds between the years 1945-1964 using the CAPM model as the theoretical benchmark showed that the funds, on average, did not outperform the simple buy-and-hold strategy. Three of the 115 funds made significantly high returns. This result is consistent with the efficiency clause that requires returns to be normally distributed. Three extraordinary observations are within the 5% significance level for a sample 115 elements. The important conclusion

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of Fama's empirical work is that the work of active fund managers is unnecessary. If returns of actively managed portfolios may be replicated by a simply buying the market portfolio, then it makes no sense to put money into these funds and incur management fees. According to Jensen (1968), the work of fund managers is therefore redundant and passive investment strategies are superior to active investment ones.

In the second half of the 20th century, the efficient market hypothesis was widely accepted as the mainstream paradigm for the next twenty years or so. The conviction about market efficiency is underpinned by Fama who wrote that "evidence in support of the efficient markets model is extensive, and (somewhat uniquely in economics) contradictory evidence is sparse." (Fama, 1970, p. 416.) Jensen believed that "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis." (Jensen, 1978, p. 95.)

The efficient market hypothesis claims that prices always reflect the fundamental value; should an asset's value deviate from its fundamental value, the deviation is temporary as the arbitrage trading of well-informed investors instantaneously eliminates any mispricing.

With the wide acceptance of the notion of market efficiency came the birth of a pricing model, the capital asset pricing model (CAPM) that assumed perfect markets. This entails a set of restrictive assumptions such as the ability to borrow and lend unlimited amounts at the risk-free rate; the market having many investors whose market size is insignificant and are price-takers, rational, risk-averse and aim to maximise their own utility. The model also assumes that information is not exclusive to any single investor, and it is available to all investors at the same time.

The capital asset pricing model (CAPM) is an equilibrium model that estimates the return of an asset by taking the beta times the expected market risk premium atop the risk-free return. Formally,

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$$E(R_i) = R_f + \beta_i [E(R_m) - R_f]$$

3. Equation

where $E(R_i)$ is the expected return of asset *i*. R_f is the return of the risk-free asset, $E(R_m) - R_f$ the expected market return less the risk-free return, else named the market risk premium (MRP). β_i is the beta of asset *i*, a measure of non-diversifiable system risk. Beta is defined as:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

4. Equation

Beta is the quotient of the covariance between the return of the asset i and the market return, and the variance of market returns.

The theoretically correct market index is a value-weighted index of the entire universe capital assets. However, Roll (1977) points out that such an index cannot be measured in practice, and argues that incomplete tests induce inference errors. It is therefore common practice to apply either the published value-weighted index of a particular market or a value-weighted index of returns on all securities listed in the market.

The Capital Asset Pricing Model (CAPM) was further elaborated by Sharpe (1964), Lintner (1965) and Black et al. (1972) to take its final form, the SLB CAPM. The SLB capital asset pricing model implicitly assumes unrestricted borrowing and lending at the same risk-free rate that is exogenously determined. Obviously this restrictive assumption lies far from reality. Conditions in the real world necessitate the existence of transaction costs which will mean that borrowing rates will always exceed lending rates. Black, Jensen and Scholes (1972) tested the CAPM under this assumption by considering a world without risk-free assets. Black's extension resulted in the more general version of the CAPM:

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$$R_{i,t} = R_{z,t} + \left(R_{m,t} - R_{z,t}\right)\beta_{i,t} + u_{i,t}$$

5. Equation

where $R_{z,t}$ is the return on a minimum variance portfolio of risky assets which is uncorrelated with market returns. This version is also known as the zero-beta CAPM or the Sharpe-Lintner-Black CAPM (henceforth SLB CAPM). The simple CAPM is a special case of the SLB model that assumes the existence of a risk-free asset in the market.

2.2. The Efficient Market Hypothesis Defied

Researchers argue about the validity of the efficient market hypothesis in the real markets, especially the validity of its strong form. There are several set-backs to the theory including the slow transmission of information, and the relative power of a few market players. The market's mechanism in adapting to change in interest rates for instance, takes from a few hours to several weeks. This is the main defect, whereas according to the EMH this process ought to be instantaneous. Only a few privileged may have prior knowledge of new laws or decisions that will affect prices. As long as actors on 'inside information' use arbitrage to take advantage of market mispricing in a discreet manner, they can avoid being detected. As soon as such trading takes place on a wide scale, it cannot be dismissed as being random.

Another example of inefficiency demonstrated by real markets vis-à-vis the theoretical environment defined by the EMH is that in extreme situations what fundamentalists consider irrational investor behaviour is actually the norm. For instance, the last stage of a bull market is usually driven by buyers (speculators) who take little consideration of the underlying value of the asset. Contrarily, the end of bear markets witness price free falls as investors hurry to close their positions regardless of the quality of the investments they hold. These observations are bolstered by the differences in stock valuation in bull markets compared to bear markets. Thus, it would make sense for rational investors to take advantage of the feigned high or low prices caused by irrational participants, by taking on opposite

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positions. In practice, this strategy is insufficient to prevent bubbles or market crashes. Rational investors are aware of the irrational behaviour of the market, and at extreme times, they will need reasons that supersede fundamental explanations to convince them that asset prices will return to fair their value. It was shown statistically, that extreme values occur more often than a normal distribution would anticipate. These extreme values are not confined to three sigmas[1]; a phenomenon financial literature refers to as a distribution's fat tail.

Opponents of the theory argue that a small number of investors exist who managed to sustain their outperformance of the market for long periods of time, in a way that overrules the role of luck. These include names such as Peter Lynch and Warren Buffett. Their strategies were always to identify markets where prices did not fully reflect available information. On the other hand, proponents of the theory argue that EMH does not rule out the success of a limited number of funds through chance. These explanations go on to explain the success of 'star' fund managers as being the result of management skills rather than stock market prediction.

Malkiel is a famous supporter of the general validity of the efficient market hypothesis. Even he, based on empirical findings, believes that some emerging markets for example the Chinese markets, are not efficient. Malkiel warns that "the Shanghai and Shenzhen markets exhibit substantial serial correlation in price trends and evidence of manipulation, contrary to the random walk theory that is expected from markets in the United States." (Malkiel, 2003 p. 23.)

The efficient market hypothesis appears to be inconsistent with some events in stock market history even in the United States. The market crash of 1987 was caused by apparently no major news; and despite that the Monday of the crash saw the S&P 500 index fall more than 20% only in the month of October. The decline seemed to originate from nowhere, only the irrational behaviour that caused the haphazard sweep through stock markets, Malkiel (2003) continues.

[1] Sigma is standard deviation. About 99.7% of a normal distribution N~(0,1) is within three standard deviations.

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Turning to the emerging markets, empirical examples were recorded by Radnai (2002), who investigated mispricing on Hungarian index futures market. Walter and Berlinger (1999) present a factor model to capture the market movements in the same emerging Hungarian market. These papers show EMH does not always hold in emerging markets, similarly to developed markets.

Investment culture in the public's imagination also refuses to believe the efficient market hypothesis. This may be attributed to a general misconception concerning its meaning. Many believe that the EMH states that a security's price is a correct reflection of the value of the underlying company as calculated by discounting the future returns. If this were true, it would mean that a stock's price accurately envisages future results. Since this is evidently not the case, many people reject the hypothesis. Nevertheless, EMH does not attempt to predict future returns. Rather, the EMH states that a security's price incorporates possible projections of future happenings, based on the best information available at the time. The EMH merely estimates the performance of a stock. If the course of events veers the true value of the stock too far away from the EMH prediction, even then the deviation does not challenge the validity of EMH.

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2.3. Behavioural Finance

To challenge the shortcoming of modern finances, namely the EMH, a revolutionary wave attempted to remedy pricing theories by relating investor decision to behavioural psychology. The term was so convincing, that Thaler noted “the term ‘behavioural finance’ will be correctly viewed as a redundant phrase. What other kind of finance is there? In their enlightenment, economists will routinely incorporate as much ‘behaviour’ into their models as they observe in the real world. After all, to do otherwise would be irrational.” (Thaler, 1999, p. 16.)

In the late 1980s, the economists started finding the dark spots in the efficient market hypothesis. There was abundant empirical evidence proving that mispricing can exist for longer periods of time. An obvious example is stock market bubbles, where stocks become extremely overpriced from time-to-time. Most economists agreed that this undoubtedly undermines the EMH, with the exception of Eugene Fama, who is still a keen supporter of EMH to this day. (Fama and French, 2011) Most empirical works critical of the EMH concentrate on specific asset pricing anomalies in the markets and attempt finding explanations for these anomalies with the aid of other social sciences, namely psychology.

Studies by De Bondt and Thaler (1985), Clare and Thomas (1995), Barberis et al. (1998), Daniel et al. (1998), Thaler (1999), Hirshleifer (2001), Barberis and Thaler (2002) and Damodaran (1989) prove the existence of market anomalies, and say that deviations from market efficiency may sustain for long periods of time – a clear violation of the efficient market hypothesis. This led to the emergence of a new stream dubbed as behavioural finance that leaned on psychological biases in their explanations. Behavioural finance integrates elements of finance and psychology to explain investor behaviour, and with this understanding it tries to understand how capital markets react to certain events.

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Hirshleifer (2001) stresses that human behaviour should be factored in when it comes to building models to describe financial markets. He argues that “security expected returns are determined by both risk and misevaluation.” (Hirshleifer, 2001, p. 1533.) Investors are irrational; and more importantly they systematically behave irrationally as there are common patterns, biases and heuristics that define investor behaviour. This is an important feature because if the investors’ behavioural departs non-systematically from the rational behaviour pattern then it would be impossible to exploit these anomalies, and earn profits.

Behavioural finance relies on three building blocks from psychology: biases, heuristics and framing effects. (Kahneman and Tversky, 1973; Kahneman et al., 1982; Hirshleifer, 2001). Biases are a tendency towards a behaviour, which is not rationally or objectively justified. Examples are excessive optimism, overconfidence, confirmation bias, conservatism and the illusion of control. (Odean, 1998) Heuristics are “rules-of-thumb” (Hirshleifer, 2001, p. 1540.) which developed in human beings during natural selection. These are simple rules, or mental shortcuts for rapid decision-making. The heuristics, however, proved to be rather misleading in financial decision-making. Examples of heuristics are representativeness, availability, anchoring and the gambler’s fallacy. Framing effects influence investment decision-making by the very question or the situation at hand as indicated in Kahneman and Tversky (1979). Examples are loss aversion and aversion of sure loss. The former denotes a higher sensitivity to losses than to gains; the latter insinuates that players tend to take on unreasonable gambles to avoid sure losses in the hope of breaking even.

Kahneman and Tversky (1979) pioneered the incorporation of irrationality into financial decision-making. They coined the term “Prospect Theory” that refuted the widely accepted “Expected Utility Theory” of Neumann et al. (1947). Their empirical findings showed that investors are loss averse, i.e. they prefer avoiding losses to making equal-sized gains. Specifically, loss averse behaviour entails double the amount of gain for a loss to be endured. This contradicts the Expected Utility Theory that assumes a symmetric attitude towards positive and negative outcomes.

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One of the primary market anomalies observed that posed a challenge to the efficient market hypothesis was the winner-loser effect, also known as long-run mean reversion. This states that “extreme movements in stock prices will be followed by subsequent price movements in the opposite direction.” (De Bondt and Thaler, 1985, p. 795) This implies that past winners will tend to be future losers, and past losers will likely become winners in the future. A possible explanation of the winner-loser effect is the overreaction hypothesis. According to this, investors overreact to a consistent pattern of news, inducing extreme movements in the price, then, as they are slow to update their beliefs prices will return very slowly to their fundamental value. This overreaction can be explained by the representativeness heuristic: investors focus more on past performance. For instance, if investors are subjected to a positive flow of news they tend to overestimate the positive effect of the news due to representativeness and excessive optimism and result in overconfidence. Prises rise excessively as a result of their optimistic behaviour. Overconfidence induces investors to see patterns in random sequences that they associate with the stream of positive news, and thus push prices up even further. Their beliefs are slow to adjust to environmental stimuli due to anchoring, and therefore they are slow or reluctant to update their expectations about the overly high prices. Eventually, when earnings reported in financial statements turn out to be not in line with the excessive pricing, a slow process of mean-reversion takes place in the stock price as investors realise the fundamentals, are disappointed and start to sell-off. De Bondt and Thaler (1985) test the validity of the winner-loser effect by creating two portfolios. One contains the winner stocks which are the 10^{th} percentile of the best performing stocks over the last three years; the loser portfolio is made up of the 10^{th} percentile of the worst performing stocks over the same period. They find that shorting the winners and going long the loser portfolio is a zero-cost position that proves to be highly profitable. Losers outperform winners by about 25% over the subsequent three years. Basu (1977, 1983) examines this strategy as well, but he separates the two portfolios based on P/E value (price-to-earnings-per-share ratio). High P/E firms are shorted against low P/E firms. The results similarly to the previous papers validate the winner-loser effect: firms with lower P/E tend to outperform high P/E-ratio-firms in

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the future. Basu also shows that low P/E ratio firms were likely to have performed worse in the past. These empirical findings appear convincing in refuting the EMH, however, the advocates of the hypothesis underline the shortcomings of these papers. First, they argue that size is a systematic risk factor that was taken into consideration in the regressions. Stocks in the ‘loser’ portfolio usually belonged to small capitalisation companies, a fact that is associated with better performance than for large capitalisation firms. (Zarowin, 1990; Chopra et al., 1992) The second claim was that ‘losers’ tended to have higher betas than ‘winners,' which meant that the winners’ better performance may be the result of an excess risk premium. (Ball and Kothari, 1989) The third objection to the tests of De Bondt and Thaler was that most of the excess returns of the ‘loser’ portfolio occurred in January, which may be attributable to the calendar effect, namely the well-known January effect (Zarowin, 1990)

Clare and Thomas (1995) tested the claims of the critics on UK data for the period 1955-1990. They concluded that only the size effect stands its ground, the other two factors proved insignificant. The size effect nevertheless was in fact quite significant, to the extent that after controlling for size, the losers ceased to outperform the winners. Contrarily, Chopra et al. (1992) found evidence that past losers (based on the past 5 years’ performance) outperformed winners significantly in the subsequent 5 years, even after controlling for size and excess risk. Although they observe a significant January effect, they conclude that it is not a result of tax-loss selling. The contradictory results of these papers show that there is no consensus on the winner-loser effect.

Francisco (1987) concluded that “it appears that the empirical anomalies on the CAPM are due to attempts to fit a linear model on a fundamentally non-linear return-risk relationship.” (Francisco, 1987, p. 45.)

2.4. The Efficient Market Hypothesis Defended

Fama coined the phrase joint-hypothesis, or “bad model problem” in reference to the mistake of De Bondt and Thaler (1985) arguing that “market efficiency is per se not

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testable" (Fama, 1991 p. 1575.) because testing market efficiency requires an assumption of an underlying asset pricing model. This may cause faulty inference of the cause of the anomaly under investigation: it may truly be a result of market inefficiency or may be due to a misspecification in the model, or the combination of the two effects. The SLB CAPM applied by De Bondt and Thaler appears to be an example of a badly specified model as it fails to explain the small firm effect. Then, how is the small firm effect consistent with the EMH? According to Fama (1991) an anomaly that violates the EMH is only temporary and would disappear shortly after its discovery given there are no limits to arbitrage trading. On the other hand, an anomalous effect can be in accordance with the EMH if it is a permanent phenomenon that can be explained by asset pricing models. Temporary effects do not persist for long periods of time. Once they are discovered, investors will profit by trading on the anomaly that will lead to its disappearance. Examples of such are the calendar anomalies including the weekend effect, the holiday effect, the time-of-the-month effect and the January effect which were shown to be significant in the past, but shortly disappeared or substantially weakened following their discovery. (Marquering et al., 2006)

In addition to the size effect, Fama (1991) recognises anomalies of book-to-market equity (BE/ME), E/P and leverage arguing that these phenomena are also rational and fit into the EMH frameset. This highlights the shortcoming of the SLB CAPM in capturing some important common risk factors. This idea was further developed into the Fama-French three-factor model. (Fama and French, 1993) The Fama-French model says that the market beta alone is insufficient to explain stock prices, as suggested by the SLB CAPM. They extend the classical model by adding the size and value premium. Therefore, size and value effect are in accordance with the EMH.

Size is determined by the market capitalisation of the company (price times shares outstanding). Value was measured by the book value to market value ratio. When the book equity to market equity ratio (BE/ME) is high, the stocks of the company are referred to as *value stocks*. Conversely, low book equity to market equity identifies

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growth stocks. The logic behind this is that higher returns are compensation for higher systematic risk. Fama and French suggest that book-to-market and size are "proxies for distress and that distressed firms may be more sensitive to certain business cycle factors, like changes in credit conditions, than firms that are financially less vulnerable." (Fama and French, 1996, p. 58.)

2.5. The Opponents Again

A more recent wave of papers appeared refuting the EMH. Huberman and Regev (2001) made an event study on the stock of EntreMed, a biotechnology company. In 1998, the New York Times reported news on EntreMed that signalled a potential breakthrough in cancer research leading to a 316% jump in the stock price on a single trading day on 5th April, 1998 (from \$12 to \$50). The stock closed above \$30 in the following weeks, showing a permanent price increase. The news, however, was not new. It was already published in Nature magazine and in the Times at least 5 months before. This event is clearly a violation of EMH, in that information was processed slowly and prices reflected the potential cancer research breakthrough with a few months lag. The story continues with the publication of another article a few months later discrediting prior results as other laboratories were unable to replicate the results. If the market were efficient as stated by the EMH, the second piece of information that appears to be no less credible than the first article ought to have led to a correction in the stock price. Instead, EntreMed still cost twice as much as before the first New York Times article.

French and Roll (1986) showed that the volatility of financial markets is significantly higher during trading hours compared to the level of volatility when the market is closed. The methodology of return calculation for weekdays was determined by the open and the close prices of the same trading day, while the weekend return was the return between the Friday close and the following Monday's open price. Their findings shed light on the asymmetry between the variance of daily returns on trading and non-trading days. Their empirical research showed that weekday variance was more than six-fold that of the variance of returns over the weekend, although one

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would expect the opposite because weekends are eight[2] times longer. The more time-lapse allows for more incoming information that in turn generates higher volatility. French and Roll say that the excess volatility is not caused by public information – which, predominantly arrive during trading hours – but rather by private information that informed investors trade upon.

Excess trading volume is one of the five problems of the Efficient Market Hypothesis, according to Thaler (1999), the rest being volatility, dividends, the equity premium puzzle and predictability. The hypothesis says that investors are rational, and markets are efficient, which implies that there is scarce private information left and trading mostly takes place for hedging purposes. Markets show more trading volume that what the rational investor – as per the EMH – would trade. (Thaler, 1999)

Odean (1999) examined the effect of excess trading on investment returns and found that investors with discount brokerage accounts trade far too much and their returns suffer from the transactional costs caused by the excess trading. Barber and Odean (2000) researched the returns of households at a large discount brokerage firm for a period spanning 6 years and account for a negative correlation between trading volume and ex post returns. Their results show that the average household underperformed the U.S. market by 1.1% annually, and by 3.7% on a risk-adjusted basis. Households trading the most underperformed by an annual 5.5%. The phenomenon of excess trading is not unique to households, but is also true in the case of mutual funds. (Carhart, 1997) Excess trading erodes returns by means of the resultant transaction costs. However, excess trading contradicts the EMH and the rational investor's expected utility maximising behaviour. The reason behind this stylised fact remains unknown. Behavioural finance explains this phenomenon by investor overconfidence. Individual investors overestimate the value of their private information (or think the information they hold is private to them but may actually be

[2] Calculating with an average 8 hour trading day, and a Friday close to a Monday open spanning over 64 hours.

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public) which induces excess trading. Barber and Odean wittingly said that “trading is hazardous to… [one’s] health” (Barber and Odean 2000, p. 800)

Volatility is the second empirical fact undermining EMH. Shiller (1981) examined whether stock price volatility can be explained by the uncertainty about future dividends. He accounted for a 5-13 times higher volatility than would be caused by variation in dividends. One potential explanation could be the change in real interest rates, but this alone was dismissed to be enough to explain the level of volatility. Another explanation was that some risk factors have not been accounted for that influence volatility. This problem was further investigated by Cutler et al. (1989) who set up a model in which stock fundamentals were used to explain stock price volatility. Their initial regressions included quantitative news proxies which explained only one-third of the total volatility observed. Then, they included qualitative political news proxies in their second round of testing. These also failed to account for the excess volatility. Also, the fact that a large part of extreme market movements occur when no major news are announced also bolster these results and undermine the EMH. Roll (1984) also attempted to capture the phenomenon of excess volatility by testing a particular commodity derivative, frozen concentrated orange juice futures. The peculiarity of the underlying product is that its production is geographically concentrated and entirely dependent on the weather: an easily and accurately measurable factor. Hence, preconditions are set to observe no excess volatility in the trading of orange juice futures. The empirical test however contradicted the hypothesis of efficiency and showed that the weather accounted for a small amount of the variations and no other factors were found to explain the remaining bigger part of volatility.

The dividend problem that contradicts EMH stems from the Modigliani – Miller (1958) theorem that governs dividend policy. They say that in the absence of taxes, bankruptcy and asymmetric information, dividend policy should not influence the value of the enterprise. In the real world, the conditions of the propositions do not hold as there are tax regimes, bankruptcy costs and information asymmetry is likely to exist. They bring the example of the U.S. tax system where shareholders benefit

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more from a share repurchase rather than receiving dividends payments. Yet companies still pay out dividends. To help understand this, one has to go back to the agent-based literature and find that due to information asymmetry companies use the dividend policy as a tool for signalling. Miller (1986) supports this by observing that a cut in dividends is often interpreted as negative news for the company.

The equity premium puzzle is another setback for market efficiency. It is an observation that average returns on equities significantly exceeded the average return of bonds beyond what may be explained by excess risk. Mehra and Prescott (1985) documented the existence of this puzzle. They tested U.S. equities for the period 1947-2000 and recorded an average real risk premium of 7.8%. (Mehra, 2003) The unsolved puzzle has attracted several explanation such as the one suggested by Mankiw and Zeldes (1991) who claim that a significant part of equity premium is attributable to the risk averse nature of investors.

Finally, predictability is another major topic of dispute between proponent of the efficient market hypothesis and the proponents of behavioural finance. The main question concerns the predictability of future stock returns? Jensen (1968) and Fama (1970) dismiss this claim outright in the seventies. Later, as the initial behaviourist critiques of the EMH started to emerge, it became obvious, that stock prices are at least partly predictable. Even Fama acknowledged that indicators like book-to-market or price-earnings ratio have a significant influence on future prices (Fama, 1991). Events like initial public offerings, mergers and acquisitions, dividend initiations and omissions, earnings announcements, share repurchases, proxy fights, stock splits and spin-offs also have predictive power for future returns. (Fama, 1998) Malkiel, the author of "A Random Walk Down Wall Street" (Malkiel, 1973) later writes a paper entitled "A Non-Random Walk Down Wall Street." (Malkiel, 2003)

Momentum is another important aspect threatening EMH. Advocates of the hypothesis argue that the winner-loser effect recorded by De Bondt and Thaler (1985) is caused by the size effect, however the problem is still disputed. The positive serial correlation in stock prices is another anomaly. Jegadeesh and Titman (1993)

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constructed zero-cost portfolios by buying past winner stocks and selling past loser stocks based on the last 6-months performance, and they held the portfolios for the forthcoming 6 months. This strategy led to an average annual excess return of roughly 12%. This anomaly persisted and motivated Carhart's (1997) four-factor model. It includes an additional risk factor to the Fama and French (1993) three-factor model, the one-year momentum. Carhart's four-factor model proved to have a very good explanatory power but did not touch on the theoretical foundations. Carhart said "I employ the model to 'explain' returns, and leave risk interpretations to the reader." (Carhart, 1997, p. 61)

Behavioural finance offered several models to explain the anomalies about predictability. The most prominent were the papers of Barberis et al. (1998) and Daniel et al. (1998). Their behavioural models offer explanation for the short-run momentum and long-term mean reversion. Fama (1998) acknowledges that these models serve their purpose in explaining the positive serial correlation in the short-term, and the long-term mean-reversion. However, they fail to explain the other anomalies. For instance, dividend initiations and omissions are events that do not cause mean-reversion on the long run. Fama (1998) argues that long-term return continuation and reversal is equally likely, and behavioural models only explain events they were built to explain, and they ignore other events, that they cannot. No behavioural model exists, which is able to account for all the anomalies, or at least for most of them.

In the past thirty years, behavioural finance has slowly overtaken the mainstream in finance notwithstanding the fact that almost every behavioural model was attacked by EMH-advocates, the evidence against market efficiency is vast. Recent articles blame the EMH for its shortfalls. (Nocera, 2009; The Economist, 2009; and Thaler, 2009) The EMH has two basic assumptions. (Barberis and Thaler, 2002) The first states that 'prices are right' and the second is the notion of 'no free lunch.' The latter is does not lie far from the truth: it is nearly impossible to earn excess returns on financial markets. The shortcoming are highlighted by the former; "prices are right." The last

10 years saw two bubbles burst, the dot-com and the housing bubble which fall beyond the ability of an explanation from the EMH.

The EMH is heavily criticised and evidence against it is abundant. Behavioural finance is usually brought up as an alternative way to understand market returns. The two have different theoretical foundations, however their predictions and recommendations about investment strategies are similarly vague. EMH reminds that one cannot beat the market, and behavioural finance says the same: although one may spot a mispricing in the market, it does not mean, that one can exploit it.

There is much more theory about aggregation of information than there is on careful observation. The standard theoretical claim is that information could not be perfectly aggregated and revealed by prices because, if it was, no traders could profit from collecting information. Grossman and Stiglitz (1980, 1982) claim that markets cannot always stay in equilibrium, as arbitrageurs do earn “private return from their privately costly activity.” They argue that price cannot fully reflect costly information. If for instance new information did not provide any returns, then no one would exert any effort to obtain the new information. This, in turn would deter new information from being incorporated into prices. This contradicts market efficiency. Grossman and Stiglitz (1980) propose a model where prices cannot fully reflect costly information because if it were the case, then those who sacrificed resources to obtain the information would not be compensated for their efforts.

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3. How Markets Work

Markets include a wide range of products that are traded on official exchanges. There are markets for equities, derivatives, foreign exchange, money markets, and commodities. Equity plays an important part in the investment universe, but is by far not the most significant asset class regarding the volume traded. However, it is a basic market that acts as an indicator of the performance of investment asset classes and therefore I confine my research to the study of equity investors, and more specifically the difference in expectations of equity investors. Therefore, cross-asset investments are beyond the scope of my research. Having narrowed down the market segment that interests us, I shall examine how markets work by introducing the important players who influence market prices. This section provides an overview of the investment banking industry to help understand the cobweb of market agents.

First, I introduce the concept of investment banking on a broad scale. It is a business that concerns providing services to clients that help them make financing and investment decisions, and execute orders in-line with those decisions. The clients may be individuals, corporations or sovereign states (governments). The financing decision refers to raising capital needed for operations through underwriting or issuing securities. The investment decision deals with dispensing excess monies to invest in good businesses in hope of maximal risk-adjusted returns.

Investment banks were part of universal banks until. From 1933 following the enacting of the Glass-Steagall Act until the 1999 Gramm-Leach-Bliley Act, the United States maintained a separation between investment and commercial banking activity. Other countries have historically not maintained such a separation. The role of investment banks also extends to assisting in mergers and acquisitions and providing additional services such as market making, trading derivatives, fixed income (FI) instruments, foreign exchange (FX), commodities and equity securities.

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Two main lines of business exist in investment banking. The first is the *sell-side* which facilitates transactions or market-making, or promotes securities within the framework of underwriting or research. The other line of business is the *buy-side* that deals with pension funds, mutual funds and hedge funds and the retail investors who are end-users of products and services of sell-side. Some banks have both buy and sell-side business lines.

It is important to understand the role and the difference between the sell and buy-sides to be able to appreciate the methodology used in defining heterogeneity of expectations.

3.1. The Buy-Side

Firms concerned with managing the assets of their clients' constitute the buy-side of the investment industry. They carry out their asset management activity by buying brokerage services from the sell-side. The most common buy-side entities are private equity funds, mutual funds, hedge funds, pension funds and proprietary trading desks. The portfolio managers (PM) employ analysts who make models for internal use, and support the investment ideas of the PMs. Their work is used in-house and do not publish their research. They rely on the research provided by the sell-side to some extent.

3.2. The Sell-Side

The sell-side of the financial services industry is the part where investment firms sell their investment services to asset management companies, known as the buy-side. The services range from activities including brokering or dealing, investment banking, advisory services and investment research.

The sales is the investment bank's sales force who call on institutional and high-net-worth investors to market trading ideas based on the research product the investment banks offers on a caveat emptor basis, which means the portfolio managers acting upon the recommendation of the sell-side cannot be held liable for giving bad

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investment advice. However, unfit investment advice can backfire in the loss of good reputation and thence loss of business in the form of lost orders. The sales desks make their best effort to make the investment ideas of their firm heard to take orders from the clients. Then, they communicate the orders to the respective trading desks that price and execute trades. The trading desks execute trades by splitting them into smaller orders which are sent directly to the exchanges or to other firms. Often the equity sales and trading activity is done by the same broker team.

The brokerage's remuneration is generated through commissions charged on the price of a stock transaction. The commission income is spread to cover the costs of the different teams serving these clients, including the sales, the trading and the equity research department.

Research includes equity, credit, strategy and cross-asset analysis. Credit research deals with the credit notes and bonds issued by companies. Other research includes strategy research that deals with the macroeconomic environment. Strategists advise external as well as internal clients on the strategies that can be adopted in various markets. Ranging from derivatives to specific industries, strategists place companies and industries in a quantitative framework with full consideration of the macroeconomic scene. Cross-asset research helps investors in making investment decisions across assets rather than within. We will focus on equity research as a specific part of research.

Equity research is concerned with publishing original reports on public companies to analyse their business and provide a sector overview. An important conclusion of research notes are the recommendations and target prices assigned to the company. Traditionally research does not generate revenues for the brokerage firm directly. However, recent developments in the industry tend towards unbundling of commission rates, which means separating the cost of trading from the cost of research. This allows clients to purchase the best quality research and pass orders on to brokers with the lowest fees, the two often being not the same investment bank.

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As research has no access but to public information it is separated by a Chinese wall from other departments that have private information on companies to prevent the crossing of insider information.

The independence of research is crucial to maintain the integrity and quality of the research. If research is part of a complex institution, oftentimes corporate finance business or the brokerage line of the bank have a contradicting interest with that of research, often pressuring the latter to present the covered companies in a favourable manner and not setting a recommendation any worse than a buy. A completely independent research activity may to lead internal cannibalisation in cases of conflict of interest. The investment bank may be trying to underwrite a secondary public offering (SPO) for a certain company and sales working hard on selling the new issuance to the clients as a great investment idea, while at the same time the research analyst may disagree with the recommendation and sees the company as expensive. To circumvent such cases, some quality research analysts have moved on to independent research boutiques that are not linked to investment banks. A famous case involving legal probation of equity research took place in the US following the bursting of the dot-com bubble. Many sell-side firms were accused of self-dealing. In addition to providing brokering service to the buy-side, these firms also engaged in investment banking services for corporations, who generally did not like to see negative opinion given on their companies. In order to prevent unfavourable research publication, corporate clients pressured the sell-side research by threatening to withhold lucrative banking business or demanded equally lucrative shares in IPOs, bribing the sell-side firms, de facto. The lawsuit brought by New York State attorney general Elliot Spitzer ended by a settlement of USD 1.4bn, but also made significant progress in cleaning up the industry in the US. It should be noted that the litigation extended only to sell-side firms and left the arguably equally culpable corporations relatively unscathed.

The research division reviews companies and publishes regular reports about their prospects giving the most detailed information available on the covered company, industry or market. The team of analysts is educated through the Chartered Financial

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Analyst qualification program that ensures a professional standard to financial analyses.

Investment houses use essentially similar methodologies to derive the recommendation put on a stock price. The methodology used in investment analysis for the determination of target prices and recommendations is governed by the in-house rules set by the respective research firms. These comply with the standards and practices set by the Chartered Financial Analysts (CFA) Institute, the most well-known professional body that deals with the education of investment analysis. Analysts working in this field are required to obtain the CFA qualification to gain the credibility essential for their work. In addition, a CFA designation ensures that the professionals are following the same rigorous methodology in their research. Furthermore, the CFA follows the professional behaviour of members that sets a standard for the ethical and professional work of analysts. For this reason, membership in the local CFA society is required by those candidates who wish to use the designation following their names. A European equivalent of the CFA Institute is the European Society of Financial Analysts Societies (EFFAS).

The interaction of agents in the investment banking industry is similar to the supply-chain of production companies. The sell-side is similar to the producer, in this case the provider of services. The buy-side, being an intermediary between investors and brokerages may be viewed as the retailer. By this analogy, the investors or end-clients who money is being invested (pension fund members, savers, high-net-worth individuals) would be the customers.

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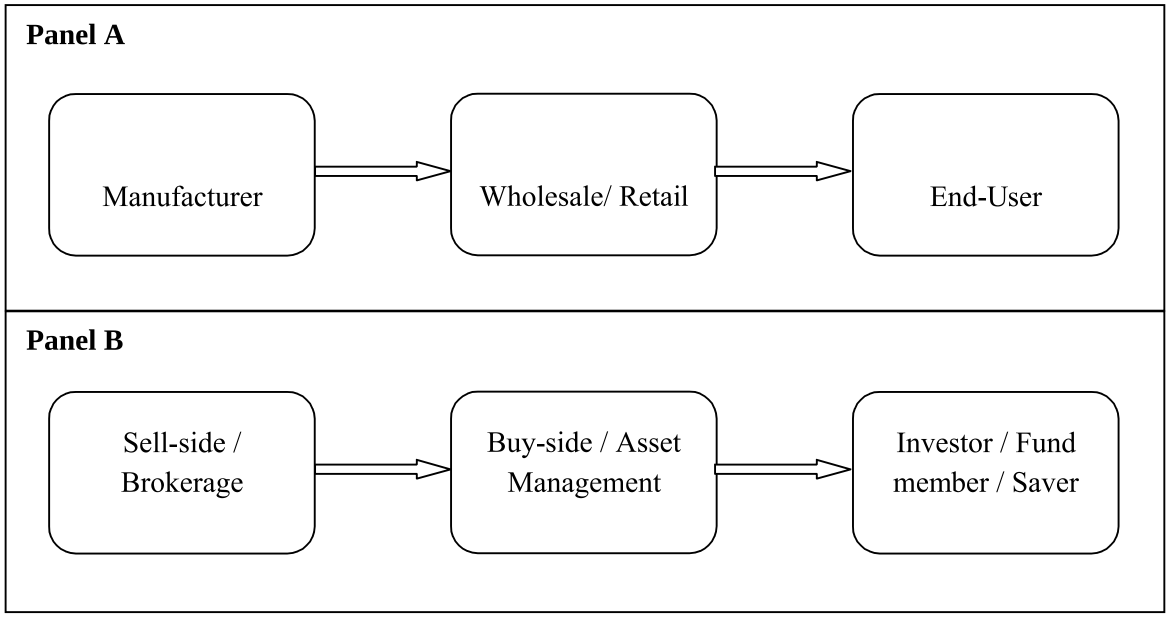

Figure 1: Panel A depicts a universal supply-chain used in manufacturing. Panel B gives the equivalent of supply-chain members in investment banking. Source: author.

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The figure below shows market actors' interaction and the direction of influence.

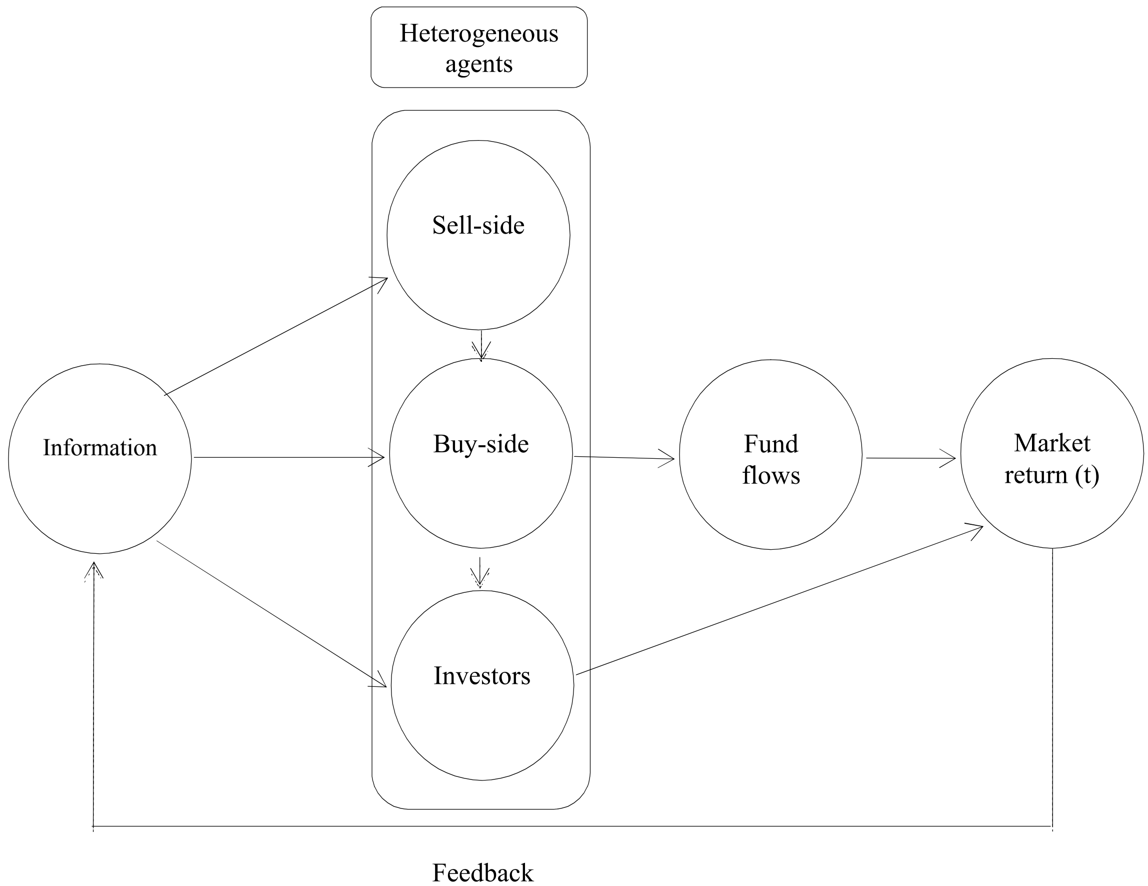

Figure 2: How market actors interact. Source: author.

Figure 2 depicts the important market actors and the direction of information flow. Information, often modelled as an exogenous factor arrives and is noted by all market agents: the sell-side, the buy-side and the investors. The sell-side research rapidly process the newly received information and interprets it within the context of investment portfolio. Specifically, the product of their analysis is to evaluate the impact of the news on a particular investment, and sales and trading market this idea to the clients: the buy-side. Their research does not reach the end-investors directly. The buy-side receives their research reports, and together with their internal analysis act upon the new information. The actions of the buy-side generate money flows that are captured by fund flow data. Investors perceive information directly from the

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primary sources, and also receive the interpretation and analysis from the buy-side. They decide on making investments directly through their own trades, however constitute the fewer portions of trades, the larger part is carried out by the buy-side (who manages the funds of the investors). The investment action of the buy-side is what essentially moves the market. The funds try to minimise transaction costs and only trade when necessary. Therefore observing fund flows given an indication of the times and amount trade takes place. My proposition is that asset returns are affected by past returns, current fund flow activity and investment activity coming directly from the investors that foregoes funds.

To understand asset pricing models, and their criteria for homogeneous expectations, we need to spot the expectations on the market. The pricing models do not differentiate between the investors and the fund managers who actually make the bulk of the investment decisions when referring to expectations. Since we are studying heterogeneity of expectations, the agents whose expectations matter needs to be clarified. Logically would assume that the expectations of all players who actually take investment decisions. Since a large portion of these trades are taken by the funds, and the measurement of the movement of monies from and to the funds can now be captured and is available to the academic researcher, then working on fund flow data to understand movement in trades is justifiable. A word of caution must be made. The effect of trading done by individual investors directly is not taken into account, and therefore results of my research need to be viewed in-line with this limitation. The heterogeneity of expectations of fund managers or portfolio managers is difficult to capture. Since their opinion is not published in an official manner like sell-side research, understanding their heterogeneity requires a poll of their opinions. One suggestion to obtain such data may be to query their forecasts one-by-one. However, academics dread such a methodology as it is tiresome, ineffective, as the professionals are often reluctant to cooperate with academic researchers.

PMI data are similar in this manner as do other sentiment and confidence indices available. These depend on the attitude of the persons questioned, often thought to be opinion leaders. And the direction of their attitude whether they are bearish or bullish

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is reflected in the index. Should the creators of such indices publish the dispersion in the opinions, then a measure of heterogeneity would be ready at hand.

Therefore, the suggestion at hand looking at the source of their opinion formation. Fund managers may argue that they form their own opinions freely, the sell-side research business however entirely builds on the fact that the buy-side relies on their research to lesser or larger extents. Therefore, having this regularly published research at hand, it is possible to observe the opinions of those who form the opinions of the fund managers. Hence, the academic literature deals with nothing more precise than the beliefs and expectations of the sell-side analysts to capture heterogeneity.

3.3. Measurement of Analyst Expectations

We have seen in the previous literature review that a number of studies show that allowing for heterogeneity in expectations may lead in certain cases to different points of equilibria than the rational equilibrium derived under the homogeneous expectation constraint. Specifically, if difference in analysts' opinions about a certain stock is observed, then the expected price of the stock is likely to behave differently than under traditional asset pricing conditions. The question now arises of how can we measure difference of opinions or heterogeneity of expectations?

Sell-side analysts regularly publish research notes on companies they cover. These include earnings forecasts for 1, 2 and 3 years ahead, and target prices and recommendations with a 1 year timeframe. These data seem to be suitable to measure the heterogeneity in analysts' opinion. In the following section I look at the different forecast measures published by analysts. All three measures aim to proxy performance, and profitability. However, each has different information content due to the methodology of deriving it.

3.3.1. Earnings Forecasts

An earnings forecast is based on the analyst's expectation of the company's future accounting pro-forma earnings per share (EPS). The methodology for calculating EPS

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forecasts is done by modelling the pro-forma accounting reports for each reporting quarter. Assumptions about growth or decline in sales and changes to margins are applied with given macroeconomic forecasts from the strategy team. Thus, an earnings forecast is derived. The earnings forecast consensus of a stock is the average (or sometimes the media) of EPS estimates provided by all analysts. The market price is often seen to adjust following the issuing of financial reports by the company depending on whether the company reported above, in-line or below consensus. (McClure, 2010).

3.3.2. Target Prices

Probably the most essential outcome of equity research is to set a target price that the analyst deems as the fair price with a 12 month horizon. Analysts use the obtained earnings forecasts as inputs to their multi-period valuation models to compute target prices.

In relation to the target price and the current market price – based on the closing price at the date preceding the publication of the research note – the upside or a downside is calculated revealing the potential move in stock price expressed as a percentage.

$$u = \frac{TP}{P_0} - 1$$

6. Equation

where, u is the upside, TP is the 12 month target price, P0 is the closing price at on the pricing day of the research report.

3.3.3. Recommendations

Recommendations are qualitative assessments of a stock’s relative value with an indication to investment action. Most investment houses have a three level taxonomy of buy, hold and sell, which refers to the recommended investment strategy. Other firms use a 5 scale measure of strong buy, buy, hold, sell, strong sell. Data compiler Bloomberg assigns numbers to each recommendation of the five categories with 1

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being a strong sell and 5 the strong buy. Then Bloomberg proceeds to average out the recommendations based on the numeric reference. This is a figure that market players observe that intends to give an indication of the average opinion that it names 12 months consensus. However, I must note that such a calculation at a first glance appears to be flawed, as the recommendations (1-5) are measured on an ordinal scale: a scale that describes an order but does not give an indication of the relative size or degree of difference between the rank order items. Central tendency measures of a group of items measured on an ordinal scale can be described only by the mode or a median; the mean cannot be defined. I propose a solution to elevate the scale of measurement. See 6.1.2 Scales of Measurement.

Finally they make recommendations using target prices. Some of the most common methodologies applied by investment houses using a three scale categorisation can be summarised below:

- A Buy recommendation is assigned if the upside is higher than or equal to the cost of equity.
- A Hold recommendation is assigned if the upside is higher than zero but lower than the cost of equity.
- A Sell recommendation is assigned if the downside is less than zero.

3.3.4. Earnings Estimates vs. Target Price and Recommendations

The literature that examines differences in analyst opinion uses earnings estimates (EPS forecasts) of analyst rather than target prices and recommendations. The reason for this is that earnings estimates are readily available from I/B/E/S, the Institutional Brokers' Estimate System data provider originally founded by New York brokerage firm Lynch, Jones & Ryan and Technimetrics, Inc., currently owned by Thomson Reuters. I/B/E/S started collecting annual pro-forma EPS forecasts from 1976 and later in mid-1980s included quarterly data that was used in academia for research. (Thomson Reuters website) Data on target prices and recommendations on the other hand is not available in a structured manner. It may be obtained from Bloomberg on a case by case basis. See 6.1 Data on Analyst Forecasts.

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In my research, I wish to examine target prices and recommendations, which I will collectively refer to as analyst forecasts. The advantages to using earnings estimates lies in the nature of earnings versus target prices. Earnings estimates try to predict the accounting earnings of a company, which is subject to different accounting policies. It is impossible to guesstimate (a mix of estimation and guessing) when a company is carrying out impairment tests for fixed assets and when, if any, impairment charges will be recorded. Target prices relate to the fundamental fair value of the stock that the analyst derives in several ways. These include a discounted cash flow method (DCF), relative valuation and SOTP approach (sum-of-the-parts). Some jurisdictions require the analyst to use at least two methods for deriving the target price. The assumption underlying is that market value will tend towards fair value in the next 12 months. Calculation of the fair value is based on public information available to all analysts alike and the basis of comparison between different target prices is thus given.

The publication date of target prices is different for each analyst, and since they are meant to given a 12 month forward looking indication of fair value, comparing target prices of different analysts to one another poses a problem. To handle this problem, one solution is to look at the upside rather than the target price per se. The upside changes on a daily basis as it is the quotient of the target price and the last closing price of that given day. In the case of EPS forecasts the problem of time-mismatch does not arise at all as all analyst give their forecast for the same date, year-end EPS targets the earnings announced in the full-year report as of 31st December.

4. The Relationship Between Analyst Forecasts and Market Returns

A fairly new area of academic research that focuses on the shortcomings of classical asset pricing and the efficient market hypothesis takes analyst forecasts as a proxy for market players' expectations. Classical asset pricing theory is based on the assumption of homogeneous expectations of investors. The assumption was a simplifying one postulating that all investors have the same expectations of the future including their forecasted macroeconomic environment, yield curves and asset risk and returns. This insinuates that informed investors interpret currently available information uniformly. This was proved to be a non-realistic assumption, and efforts to release this assumption included finding ways to capture heterogeneous expectations.

The expectations of investors are difficult to define, and even more difficult to capture per se. It is not clear from the literature what degree of homogeneity is required, or in what aspects must investors remain homogeneous for the asset pricing model to hold. Furthermore, investors are also a broad category. We may agree that in order to define investors whose expectations the model considers homogeneous, we should take those individuals who make investment decisions. By this token, pension-savers are not the investors, but the portfolio manager of the pension fund acting on their behalf is the investor in this case. However, a lot of cases are vague. Should we consider the expectations of individuals who invest into investment funds, already making an investment choice when choosing amongst the different types of investment funds; or should we consider the expectations of portfolio managers at the investment funds who will make investment decisions across-assets, and portfolio allocations within an asset category. 0

Assuming we resolve the issue of the loosely defined category of investors by including all those who take an investment decision, albeit with different weights. The next obstacle is capturing the expectations of these investors. Since there is no

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official organised tally of the expectations of investors, a researcher needs to obtain their opinion one by one either by a questionnaire or by any other means. The lack of motivation to disclose their opinion is a serious obstacle making the capturing of the expectations of the innumerable investors an unfeasible exercise for the purpose of academic research. Therefore, taking equity analyst opinion as a proxy for investor beliefs is the second best option academia has come up with to capture heterogeneity of expectations.

It is unclear whether the assumption of homogeneity was instigated for mathematical reasons, with full-knowledge of its limited practical truth, or it was part of mainstream belief, that expectations are homogeneous is a topic of debate. The dropping of this assumption means that we model the market with agents (investors) who differ in their information-processing abilities and draw different inferences from the same information, or are not exposed to the same information which created informational asymmetry. Researches that applied agent-based modelling to capture the heterogeneity of investors' expectations included Hommes (2005), Haltiwanger and Waldman (1985) and Stout (2004).

These papers largely assume two types of agents one applying more sophisticated and rigorous analysis, the other being less thorough. Haltiwanger and Waldman (1985) differentiate between sophisticated and naïve investors, Thaler (1999) names them rational and quasi-rational investors and Nagel (2005) used the terms sophisticated and less-sophisticated with reference to their applied methodology of stock picking. Other researchers differentiate between investors who base their decisions on fundamental analysis and those who depend on technical analysis, hence the terms fundamentalists and chartists.

Following Haltiwanger and Waldman, the sophisticated investors are the rational ones, with unlimited computational abilities, their opinion formation leads their expectations to be mostly right. On the other hand, naïve investors have limited ability to form correct opinion and therefore their expectations frequently contain error. Thaler (1999) shows that the simplest two-player model will have a market

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equilibrium that will likely differ from the one set in a homogeneous expectations framework. In Thaler's model there are two assets, X and Y, which have the same value. Sophisticated investors are aware of the fact that the value of the two assets is the same; the naïve investors think that X is worth more than Y. Thaler shows that the equilibrium will change if some non-trivial conditions are not met. These include the following non-exclusive conditions. Most investors should fall into the sophisticated category, which means that they can remain solvent. Naïve type investors cannot own a substantial part of total assets. Short selling constraints apply only to naïve investors. This is necessary to enable the sophisticated ones to counter-balance the mispricing caused by the trading activity of naïve investors. In practice, these conditions are not likely to be met causing the equilibrium price to differ from the homogeneous case. (Thaler, 1999)

In models that assume Bayesian learning, heterogeneity does not alter the equilibrium of the homogeneously rational-agent model as investors update their expectations based on new information and make their new beliefs using conditional probabilities. (Cyert and DeGroot, 1974; DeCanio, 1979)

Haltiwanger and Waldman (1985) agree with this, but they also underline the necessity to examine more thoroughly the interaction of heterogeneous agents. Learning models do not work in the case of non-recurring events, nor in the case of agents faced with a situation for the first time with no prior experience which makes investment decision-making cases unique. Also, another and more severe shortcoming of the learning preposition is the resultant rational equilibrium is that it is not supported by empirical evidence. (Arrow, 1981)

Haltiwanger and Waldman (1985) examine different scenarios influenced by the two types of agents and observe where the equilibrium. In each scenario agents make irrevocable decisions including only two options. The researchers identify three base cases. The first examines congestion effects. Common examples include road congestions that entail decisions by drivers on which route to take to minimise travel time, or the decision young individuals take about their higher education. The

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common factor behind these situations is that the utility function of individuals is decreasing with the increase in the total number of people taking the same decision. In these instances, sophisticated individuals anticipate the behaviour of naïve ones and tend to neutralise the bias, therefore the investor community as a whole will act rationally, as if all members were sophisticated. The second case considers the effects of synergy. This entails an increasing utility function with the increase in the number of peers making the same decision. Examples of such can be found in any type of networks where sophisticated agents again anticipate the behaviour of the others, but this time due to synergy, they are motivated in mimicking the biased behaviour. As a result, the equilibrium will represent one resulting on an all naïve-agent market. The third case distinguishes a situation in which reputation is important allowing for both types of equilibria to develop. In the above examples, two instances result in equilibria that are different from the rational one once we allow for at least two types of agents who are heterogeneous in their expectations. If heterogeneity were measured on a continuous scale similarly to real life, the situations become more complex, but it is almost certain that the equilibrium will differ from the rational one. This is particularly interesting when applied to investments, where heterogeneity is present, but fundamental analysts base their models on traditional asset pricing that does not take heterogeneity into consideration. Thus, expected stock returns will not coincide with the returns predicted by the analysis.

4.1. Heterogeneous Expectations in Equity Markets

A wide range of published papers tackle the issue of heterogeneous beliefs in the context of asset pricing. Most papers focus on whether the differences in analyst opinion have a significant effect on future stock returns. The contradicting findings reported give no resolution to this question and empirical evidence still provides confusing explanations. Most studies measure heterogeneity in analyst opinion by the dispersion of analysts' earnings per share forecasts provided by I/B/E/S. Using analysts' target prices and recommendations is another viable method less widely used. Papers such as Stickel (1992) and Hong (2000) suggest EPS forecast as being

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the appropriate measure as analyst compensation is linked to their ability to forecast earnings correctly. I believe that this proposition is mostly stemming from the difficulty to obtain target price and recommendation data, whereas I/B/E/S is the service provider that specialises in gathering EPS forecasts of analysts and makes them available to academia –albeit for a fee.

Diether, Malloy, and Scherbina (2002) (henceforth DMS) and Johnson (2004) report a negative relationship between the dispersion of analysts' earnings forecasts and future returns, and show that dispersion in earnings forecasts is not suitable as a proxy for risk. Diamond and Verrecchia (1987) and Hong and Stein (1999) found no significant relationship between the two, and several other researchers like Malkiel (1982), Barry and Brown (1985) accounted for a positive correlation and consider dispersion as a possible proxy for risk. In response to the contradicting evidence, Qu et al. (2004) argued that the mixed results were due to the wrong definition of the risk measure. They said that it is the variability in dispersion and not the level of dispersion per se that is important. They show that the variability of analysts' earnings forecasts – being a systematic pricing factor – is a good proxy for risk. To understand heterogeneity, first we have to understand who the market participants are, what motivates their investment decisions and how is information dispensed to them and processed by them, to understand how their heterogeneity reflects in asset prices.

The most accepted proxy for heterogeneous expectations - or the differences in opinion, which is based on earnings forecast, is the dispersion of analysts' earnings forecast. DMS defines it as the standard deviation of earnings forecasts divided by the absolute value of the mean earnings forecast. Surprisingly only a few studies are concerned with target prices and recommendations, especially in connection of heterogeneous beliefs. According to Gleason et al. (2007) though, the accuracy of analysts' earnings forecasts and the accuracy of analysts' target prices are related.

Other possible measures are mutual fund ownership (Chen et al., 2001), turnover (DMS), trading volume (Lee and Swaminathan, 2000) and institutional ownership (Nagel, 2005). These alternative measures are highly correlated with the dispersion of

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analysts' earnings forecast, and the results obtained using the other proxies bolster the results of DMS.

4.2. Upward Bias and Subsequent Lower Returns

DMS and Johnson (2004) use different theoretical foundations, but both came to the same conclusion, that there is a negative correlation between analysts' earnings dispersion and future stock returns. DMS take a behavioural approach, while Johnson's model assumes completely rational agents. DMS relies heavily on the Miller (1977)-model. In fact, their work is consistent with every behavioural model, in which some negative information is withheld from the market, causing upward bias in the prices. First, the Miller-model and some other papers will be presented, which also explain the overpricing, then the work of DMS and Johnson (2004) will follow suite.

Miller's model is based on the heterogeneous nature of agents' beliefs. This means that agents have different valuations about the current price of a stock. Based on these valuations we can divide them into two groups. To the first group belong those, whose valuation is at least as high as the current price. These are the optimists, who would like to buy or hold the stock, and in the second group there are those, who would like to sell it, the pessimists. Miller argues that when there are short-sale constraints on the market and due to these constraints pessimists cannot sell, optimists are overconfident and think that pessimists did not trade because their valuation equalled the market price. As a result the current price will be higher than on a well-functioning market, where the price equals the average opinion, and the bigger the difference between the valuations of the two types, the higher will be the price difference. This upward bias will cause lower future returns. The findings of Nagel (2005), Lamont (2004) and Harrison and Kreps (1978) also support the Miller-model, namely that short-sale constraints lead to the overpricing of the stock, and thus to lower subsequent returns. Nagel (2005) uses institutional ownership as a proxy for short-sale constraints. He differentiates between two kinds of impediments of selling short: indirect and direct constraints. Indirect short-sale constraints arise when short-

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sale is not allowed on the market, and there are direct constraints when shot-selling is just costly. Furthermore there are two types of investors: sophisticated (those who know the true value of a stock) and less sophisticated, naïve investors. Institutional investors are considered to be the sophisticated ones. Suppose the underlying stock becomes overpriced. Now, because there are indirect short-sale constraints, the price can only return to its true value if those who actually own the stock decide to sell it. Note that if there were no indirect constraints sophisticated investors would short-sell and bring the price back to its true value. The higher the ratio of sophisticated traders among those who own the stock, the less the upward bias will be. Once again, because sophisticated investors are more likely to be institutional investors, low institutional ownership causes bigger mispricing. The effect of direct constraints produces similar results, because short-sale costs tend to be higher for low institutional ownership. It may also be interesting to have a look at the work of Harrison and Kreps (1978). They built a model of heterogeneous expectations, and showed that the market price can be even higher than the highest valuation of investors. This can happen when investors exhibit speculative behaviour, which means, that they are willing to pay more for a stock than its value based on the present value of future dividends, because they expect to sell it later for a higher price to someone, who has higher valuations in the future. Nagel (2005) describes a simplified example of the Harrison-Kreps-model. In his example there are two types of investors, A and B. He assumes a three-period model, where there is one information signal which can be good or bad both having equal probabilities of occurrence. Both types of investors react to this news signal in the same way, if it proves good, they value the stock at 300, if it turns out to be bad, then they are willing to pay only 100 for it. At time 0 both investors value the stock at 200. The only difference between them is that investor A perceives the signal at time 1, whereas B only at time 2. Now, at period 1 there are two possibilities. When the news is good, then the price will be 300, because when there are short-sale constraints, always those with higher valuations set the price. So in this case A will buy the stocks from B, and will hold all the stocks. When the news are bad, then the direction of the transaction is the opposite, A will sell his stocks to B for 200. The interesting thing is that the

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average price is 250, so in the absence of a discount factor at time 0 both of them are willing to pay 250 for the stock, though they know that the expected value at time 2 is 200. Note that when the information asymmetry is resolved at time 2, investor B suffers a loss of 100 if the news was bad on the market. This happens with 50% probability, so B can expect an expected loss of 50, which equals to the magnitude of the initial mispricing, the difference between the time 1 valuation of 250 and the time 2 valuations, 200. This way, in the presence of short-sale constraints, speculators believe that no substantial information is released until time 2. It is important to note that in order to this situation to arise, investors are modelled using the differences of opinion concept. (Varian, 1989)

Although all information about the other type of investor is common knowledge, investors ignore the rationale behind their behaviour, because both A and B believe that they know better than the other. In the first case, for instance, when type A receives bad information, B knows this, but ignores it, because B is confident that no relevant information is published before time 2. behaviour can make prices even higher than the highest valuation of investors.

McNichols and O'Brien (1997) examined analysts' behaviour when making forecasts and recommendations, and found that due to their incentive structure they avoid disclosing negative news about a firm they are covering, and also they are more likely to stop covering firms, which perform badly. This behaviour implies that favourable news prevails and forecasts are biased upwards.

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4.3. Negative Correlation Between Dispersion and Expected Returns

DMS built their model based on Miller (1977). They measure the differences of opinion by the dispersion of analysts' forecasts. Their hypothesis is that the higher the dispersion in analyst forecasts, the lower the expected future returns will be. They use triple-sorting and a multifactor specification to prove their results, namely to show that buying the stocks that belong to the lowest dispersion group and shorting the highest dispersion group is a profitable strategy. They claim that their results are robust and stable in time. The authors also provide empirical evidence that dispersion is positively correlated with widely-used risk measures, such as the market beta, earnings variability and earnings volatility. However, since high analyst forecasts dispersion means subsequent lower returns, it cannot be interpreted as a proxy for risk, they argue. The results are stronger for smaller stocks, which is in-line with the Miller-model, because small stocks are the ones most likely to face short-selling difficulty. DMS performed sub-period analysis and found that for the 1992 to 2000 time period the results are less pronounced than for the 1983-1991 period, which is again consistent with Miller. They formed portfolios based on size, book-to-market ratio and dispersion and also on size, momentum and dispersion to see if the results are not only a pure size/book-to-market/momentum effect. To test whether the Carhart (1997) four-factor model can explain this effect, stocks were divided into five groups based on the level of dispersion. On the one hand, short-sale costs decreased compared to the earlier period, leading to reduced short-sale constraints, and on the other, information about firms was more readily available and of better quality, which might have reduced the magnitude of differences in opinions. Both weaken the effect described by Miller (1977).

Johnson (2004) relies on a multiple-signal model. First he decomposes the risk factor proxied by the variance into two parts: fundamental risk, which is the stochastic component, and the parameter risk, which captures the uncertainty about the current value. The dispersion of earnings forecast proxies only parameter risk. He models a

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firm's true value process with an unobservable diffusion process, and assumes that there are N noisy signals about this value process that provide investors with information. The main idea here is that parameter risk is idiosyncratic, and hence is not compensated by risk premium. The Merton model is widely-used for pricing corporate debt, and is based on the classic option pricing formula of Black and Scholes (1973). The level of leverage is important, because as it increases the residual equity claim becomes more option-like, and it becomes more sensitive to uncertainty, which enters via the parameter risk. In other words, for a levered firm more diverse opinions increase the dispersion in analysts' earnings forecasts, which enlarge the parameter risk and since the risk premium is unchanged it leads to lower subsequent returns.

DMS emphasise that their findings may not be entirely caused by Miller's short sale constraint hypothesis, they claim if market participants are boundedly rational and there are limited arbitrage possibilities, any friction that withholds negative information from the market may cause upward bias in the price. McNichols and O'Brien (1997) documented such withheld unfavourable information, and Thaler (1999) draws attention to the fact that even in a very simple model, certain nontrivial conditions have to be met in order to arbitrageurs eliminate the mispricing. According to Shleifer and Vishny (1997) arbitrageurs avoid extremely volatile positions. Denis and Dimitri (2002) point out that arbitrageurs may face financial constraints, and when market breadth is low, short-sale constraints arise (Chen et al., 2001). Note, that in this case, when there are withheld negative information, and limited arbitrage, there is no need for short-sale constraints to explain the negative correlation between dispersion and subsequent returns.

4.4. No Upward Bias

Diamond and Verrecchia (1987) reflect upon the Miller (1977) model, and argue that assuming rational agents, the asset price remains unbiased. In their model there is a risk-neutral market-maker, who faces no inventory costs or constraints and makes zero profit due to pressure from competition. The traders are risk-neutral, and

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depending on their information level, they form two groups. A trader is uninformed if he only has public information, and informed if he in addition owns private information as well. While informed individuals know the true liquidation value of a stock, uninformed ones only make inferences about it.

This model relies heavily on the special role of the market-maker. In order for the market-maker to break-even, he has to lose when transacting with informed traders and profit from transactions with the others. This must hold every time he has sets a bid and an ask price and since the price is essentially the same for the two types of traders, those with more information will do better trades than the others. Therefore the break-even condition can only hold, if the market-maker systematically incurs losses from trading with informed traders, and profit from transacting with uninformed ones. To act as described, the market-maker needs to know the conditional expectation of the value of the underlying asset conditioned on all past trades and all information about the current trade. This set of information includes short-selling costs and restrictions, and also the rules how informed and uninformed traders act when they face these short-sale constraints. In summary, the market-maker knows exactly the trading constraints on the market and also the traders' reaction to these conditions. This makes it possible for him to set prices with the previously described properties, which are unbiased. Note that prices will be unbiased only because the market-maker's information set includes the knowledge about short-sale constraints. In the basic Miller (1977) model investors are uninformed of these constraints, and the optimists make their decisions as if the market were efficient, the prices however will be biased. While the model of Diamond and Verrecchia (1987) appear to be theoretically flawless, it lacks support from empirical evidence.

4.5. Dispersion of Forecasts Proxying Risk

Several papers document that dispersion of analysts' earnings forecasts is positively correlated with future returns and also with risk measures such as the market beta. Malkiel (1982) argues that dispersion is actually a better proxy for risk than the traditional market beta, because he accounts for a higher correlation coefficient

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between dispersion and expected future returns, than between the beta and expected returns. This result contradicts the findings of DMS. This may be attributed to the methodology applied. The expected future returns are derived using the dividend discount model, while DMS and Johnson (2004) used ex-post returns. Malkiel (1982) estimated his model during 1960s and there is evidence (Bodie et al., 2003, p. 403.) that in the 1950-1999 time period the two valuations differ substantially, indicating that their results are data specific.

Barry and Brown (1985) built a theoretical model of differential information, which predicts a positive relationship between the divergence of analyst opinions and excess returns. They argue that the increase of the relevant available information has two consequences at the same time. On the one hand it reduces the divergence of analysts' opinion, and on the other hand it reduces the estimation risk. Lower estimation risk means lower risk, and according to the basic risk-return trade-off it implies lower subsequent expected excess returns. In this way divergence of opinions can be used as a proxy for systematic risk. The main set-back to their model is that it lacks empirical evidence, it remains only a hypothesis.

4.6. Variability of Forecast Dispersion as a Proxy for Risk

Qu et al. (2004) argue that the contradicting results may be due to the use of the wrong risk measures. They suggest the use of the variability of analysts' earnings forecasts dispersion instead of the usual level of dispersion alone, and show that this new measure is a good proxy for systematic risk. Furthermore, this measure contains a new dimension of risk, orthogonal to the traditional four factors used in the four-factor model of Carhart (1997). Qu et al. (2004) claim that dispersion has dual properties: it carries information risk, and measures the differences of opinions across analysts. Information risk is a complex concept; it can be decomposed into information asymmetry and estimation risk, that measures the uncertainty about the current stock value. They show that in order to capture the estimation risk one should use the variability of dispersion as a proxy, whereas to proxy for the differences of opinions the measure to use is simply dispersion. The model of Qu et al. (2004)

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provides a synthesis of the existent papers in this field. It supports the concept of DMS and others who claim that higher dispersion leads to lower expected returns, but it is also able to find the risk aspect of dispersion.

Qu et al. (2004) proceed with empirical tests to determine the role of variability of dispersion as a risk measure. They define information uncertainty annually as the standard deviation of the monthly forecast dispersion. First they show that higher level of information uncertainty is indeed compensated by higher expected return. Next, the fact that it is highly correlated with the standard four-factors of Carhart (1997) makes it a systematic risk factor. At the same time it cannot be entirely explained by these four-factors, a substantial amount of its return variation remains unexplained. This suggests that information uncertainty has a unique risk component. When adding it to the traditional four-factors, and thus estimating a five-factor model, in most instances it carries significant loadings, which means it is a priced risk factor.

4.7. Target Prices and Recommendations as Proxies of Opinion

Brav and Lehavy (2003) provide empirical evidence that target prices are informative, both conditional and unconditional on earnings forecasts and recommendations. Gleason et al. (2007) report of a positive relationship between the accuracy of analysts' earnings forecasts and target prices. Other studies show no relationship between the forecasts and returns such as Bradshaw et al. (2006), who examined the connection between earnings forecasts, target prices and recommendations. Their argument is twofold: first they claim that calculating target prices is a lot more difficult and different from estimating future earnings, and the connection between the two is not so obvious as Gleason et al. (2007) stated. Second, analysts are motivated in their remunerations to make accurate earnings forecasts and recommendations, but they have no incentives to do so with target price forecasts. So if they behave rationally, they will spend less effort making accurate target price forecasts, and at the same time even if they were able to give accurate estimates without any costs, they would be likely to hold it back, because they do not want to give away their superior information to the market freely caused by conflicting

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incentives. The authors' empirical findings also bolster this theory; their results indicate that earnings forecasts and recommendations carry substantial information about future prices, but target prices are irrelevant. Gleason et al. (2007) agree that this theory may be plausible, but their empirical results indicate quite the contrary; earnings forecasts and target prices are positively associated. Since earnings forecasts undoubtedly contain information about subsequent returns, target prices should also have this property. Moreover, if recommendations are formed from target prices, then because they are informative, target prices should also not be any less meaningless. If target prices are informative and positively correlated with earnings forecasts, then it can be easily used to proxy for the differences of analysts' opinions. If on the other hand there is no such relationship between target prices and earnings forecasts, it may still be used as a proxy, because I am primarily interested in the dispersion and not the level and accuracy of estimations. For recommendations it has been shown in several studies (Womack, 1996; Barber et al., 2001; Mikhail et al., 2004; and Loh and Mian, 2006), that they do carry significant information about future prices. These papers show that the work of sell-side analysts is not redundant, and those analysts whose earnings forecasts are accurate are likely to provide profitable recommendations. Although Mikhail et al. (2004) have found that trading strategies utilising recommendations generate excess returns, they proved to be unprofitable once transaction costs are accounted for. From a behavioural aspect it is interesting to note that the market reacts to the publication of recommendations on the following five days of the report, but this reaction is incomplete; investors under-react to the news in the recommendations, and there is a post-recommendations-announcement drift in the following three months (Mikhail et al., 2004). Womack (1996) found evidence for under-reaction, and his results show a more pronounced drift for sell recommendations. Daniel et al. (1998) explained post-event under-reaction with a behavioural model. In their model, informed investors suffer from two biases, overconfidence and biased self-attribution. The first makes them overvalue their private information; biased self-attribution makes them assign too little weight to the importance of publicly available information. According to them, the two biases

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combined will first cause an under-reaction, then a short-term continuation and finally long-term reversal.

Klobucnik et al. (2012) suggest that target price changes are more important than recommendations when the latter are issued with large contradictory target price changes. Contradictory analyst signals could be when a buy recommendation is reiterated and there is a substantial cut in the target price. They find that target price changes do not cause abnormal returns within each recommendation category. They claim that contradictory analyst signals neutralize each other, whereas confirmatory signals reinforce each other. To understand why abnormal returns follow the direction of target price changes rather that of a contradictory recommendation, Kanne and Kreutzmann (2008) imply that analysts are in some situations either unaware of the information in their own target price forecasts or use target price changes to signal private information to the market if outside pressure prevents them from changing the recommendation. They show that overall, analysts' recommendations go wrong when they are issued with large "contradicting" target price changes and are correct and significant when they agree.

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5. The Relationship Between Investment Fund Flows and Market Returns

The importance of investment funds has risen in last twenty years because of the many advantages they offer to individual investors. They provide opportunity for portfolio diversification with professional asset management with reduced asset management costs (Alexakis et al., 2004) due to economies of scale achieved. Moreover, investment funds provide liquidity to the market the importance of which was focal after the latest financial crises when understanding the different aspects of liquidity became crucial for most financial institutions. Therefore, data on fund sales and redemptions – dubbed as "fund flows"– may offer valuable insight into liquidity and factors influencing money movements (Brand and Ringrose, 2009). Investment fund flows are the net money in and out flows that investment funds suffer due to investors purchasing or redeeming fund shares.

In recent years, several academic papers studied investment fund flows and their effect on prices and yields as investment funds might contribute to the stabilization or destabilization of the financial markets (Bengtsson, 2009). Furthermore, money in- and outflows to investment funds may have an impact on equity returns as it was shown by Fridson (2000), on commodity prices like gold prices (Warther, 1995) and on stock prices as well (Warther, 1995; Fortune 1998). Moreover, since it might influence the stock prices it might have an effect on stock market returns, as shown by Warther (1995) and Goetzmann and Massa (1999). If the different relationships are true, then fund flow data can be a useful tool in developing trading strategies as it was done in a study conducted by Deutsche Bank, or as an input into models serving portfolio management with regards to asset allocation decisions into different assets and different regions (Meyer, 2010). In addition, fund flow data might play an important role in spreading crises (Jotikasthira, 2011).

Prior research shows that fund flows have a complex effect on financial markets and only a small part of it has been explored yet. There are still a lot of questions to be

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answered and lot of aspects that need to be examined. At a first glance, the relationship between fund flows and asset returns appear incredibly simple. Investment funds experience money inflows that they have to spend on securities. Therefore, fund inflows reflect additional demand that results in an increase in asset prices. However, the question arises, why do inflows occur? Is it possible that they are driven by past performance? Questions that this paper seeks to tackle include investigating the relationship between returns and fund flows in the Emerging European Markets. Are returns and flows correlated? Does information on past and current returns have any predictive power for forecasting future fund flows? Do the contemporaneous and past fund flows predict the future market performance? This paper will solely concentrate on the aggregate equity fund flows obtained from the Emerging Portfolio Fund Research database and stock index returns. It is also important to mention the drawback of researching such a relatively new topic that stems from the scarcity of publicly available information. Obtaining data for this research was expensive and even then few data remained after data cleansing. Therefore, the focus of this paper was on the Polish and Czech markets, as representatives of the EME region.

5.1. Investment Funds

The main objective of investment funds is to pool money from individual investors and invest the aggregate into different instruments. Thus, investing in funds is an efficient way for diversification of one's holdings and helps in avoiding losses caused by the failure of individual companies (Bodie et al., 2005). Funds have the advantages of being able to buy and sell stocks in large quantities therefore the cost of investing can be significantly reduced compared to the transaction costs of individual investments due to economies of scale.

The management of the assets held by investment funds is usually contracted out to professionals in order to provide the individual investors better and more stable returns that they would be able to accomplish themselves (Chatfield-Roberts, 2006).

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Fund managers decide upon how the money of investors will be allocated across different types of assets in-line with the fund's objectives.

Investment funds can be classified is several ways. First, the management strategy of these funds distinguished actively or passively managed funds. Actively managed funds aim to outperform the benchmark index by spotting mispriced securities and timing. Passive portfolio management rests on the belief that markets are efficient, and it is not possible to significantly outperform the market on the long run. In this framework, the fund manager of a passively managed portfolio tries to reproduce the performance of the market index.

A second classification of funds is the open-end and close-end investment funds. In an open-end fund there is no restriction on the amount of shares the fund will issue if demand is sufficiently high. Also, open-end funds buy-back shares when investors wish to sell them at a price corresponding to the net asset value (NAV) of total assets under management (AUM) per share. Close-end funds on the other hand issue a fix number of shares that remains unchanged with a few exceptions. Some closed-end funds can be publicly traded investment companies that raise a fixed amount of capital through an initial public offering (IPO). The funds are then structured, listed and traded like a stock on a stock exchange; these are dubbed the "Exchange Traded Funds."

A third attempt to classify funds bases taxonomy on the assets the funds invest in. Here we may distinguish money market, bond, equity and mixed funds. According to the European Fund and Asset Management Association (EFAMA) equity funds are those that have at least 85% exposure to stocks. Those investment funds that have more than 90% exposure to fixed income securities are classified as bond funds while money market funds are those that invest in securities with duration less than a year. Mixed funds invest in more than one of the aforementioned asset classes.

Investment objective is another criterion for classification. There are income and growth funds. Income funds invest in assets that provide the investors with stable income over a long period of time, whilst growth funds invest in securities with a

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high growth potential that provide capital appreciation rather than a steady level of income. Some investment funds can be classified into both groups (Chatfeild-Roberts, 2006). A more elaborate classification is conducted by the Investment Company Institute in the US that identifies 21 fund classes based on the fund's objective (Remolona et al., 1997) such as aggressive growth funds or tax-exempt funds for instance.

Finally, a classification based on regional scope is the one that we are the most concerned with. Local funds only invest in the assets of the local market where they are domiciled. Regional funds invest in several countries that are strongly related to each other and the global or international funds which invest all over the world (Kaminsky et al., 2001). We shall be looking at funds that invest in a certain country and track money flows into those funds.

5.2. Fund Flows

Fund flows are the net of all cash inflows and outflows that investment funds experience over time. The calculation of fund flows does not encompass the performance of the assets in the fund: only share redemptions (outflows) and share purchases (inflows) count.

Investment funds receive new cash when the investors purchase fund shares and suffer cash outflows as a result of the sale of fund shares. Net cash inflows can be either maintained as cash balances or can be invested in new securities according to the fund's investment objectives. In this manner fund flows influence the trading activity of funds. (Dubovsky, 2010). Fund managers might be forced to buy stocks as a result of money inflow that increased their liquidity and this might affect share prices. (Bengtsson, 2009). It was observed that money inflow chases superior past performance as recorded in (Cha and Kim, 2007) and by the same logic, money outflows tend to follow poor past performance. Huge aggregate money outflows forcing the funds to sell their assets rarely took place (Fortune, 1998); however the recent financial crisis proved to be an exception.

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Why should investors and financial institutions care about fund flows? Researches in this field have shown that the money in and outflow can have significant effects on several economic indicators such as interest rates (Fortune, 1998), yield spreads (Warther, 1995), gold prices (ibid.) and most importantly on stock prices (ibid., Fortune, 1998) and on returns on stocks (Warther, 1995; Goetzmann and Massa, 1999). Gross inflows can increase trading, that increases the transaction costs mainly because of the costs of providing liquidity (Edelen, 1999). Investors and market analysts watch fund flows to measure investor sentiment within specific asset classes, sectors, or for the market as a whole. Its importance has been already recognised, and the mutual fund flows are considered to be an economic indicator.

Analysing fund flows can take the form of a micro and a macro approach. At a micro level, the relation between individual fund performance and the flow of money into the fund is investigated. Investors decide on where to invest their money by evaluating past performance of different investment funds. Thus, we would expect that inflows will go into funds that have achieved the highest returns in the preceding year, and the underperforming funds would suffer investor money outflow. On the other hand, some empirical studies showed that investors actually do not sell the shares of the funds with the poorest performance. (Barber et al., 2000) We can explain this by investor reluctance to realise incurred losses. Despite this, the financial literature agrees that at the micro level past performance drives fund flows. (Ippolito, 1992 and Alexakis et al., 2004).

The macro approach on the other hand studies aggregate flows of all investment funds. This approach was first introduced by Warther (1995). He realised that money flows into individual funds are usually reallocations between the funds, i.e. one fund's outflow is another fund's inflow and is unlikely to change security prices. At a macro level, flows between funds net out. This gives the basis to examine how grand-scale money movements affect different aspects of the economy. At the macro level, investors consider the performance of entire markets when deciding on asset allocation rather than the performance of individual funds. In this paper, we take the

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aggregate approach to analyse the relationship between the market performance and the aggregate fund flows.

5.3. The Relationship Between Fund Flows and Security Returns

The financial literature presents several theories that try to capture the essence of the relationship between fund flows and returns. Some support the idea of a flow-return link while others reject it. In this section we introduce the most relevant theoretical explanations on fund flow-return relationship.

5.4. Proponents of Independency

The general equilibrium theory (e.g. CAPM) suggests that in an efficient capital market, share prices change only according to the new information on fundamental economic factors (e.g. economic growth, interest level etc.) and individual factors (e.g. earnings, future prospects etc.). However, in this theoretical framework share prices may deviate from their fundamental equilibrium values for short intervals; but those deviations are sporadic and last for short intervals (Bengtsson, 2009). Any exogenous shocks that affect security returns and fund flows will create a new equilibrium without any dynamic implications for the following periods (Fortune, 1998). Therefore, based on the general equilibrium theory, fund flows cannot affect future stock prices, only the present ones. Therefore in GET models prices are independent in time.

5.5. Proponents of Dependency

On the other hand, other theories suggest that returns influence fund flows which influence future returns. Investment sentiment and momentum trading suggest that past returns influence present flows and future returns. While price pressure, information revelation and the noise trader concept imply that present returns are affected by past flows. The table below summarises the theories and the relationships they support. r is the return of assets and f is the rate of fund flow/NAV.

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	r_{t-1}	r_t
f_{t-1}		Price pressure Information revelation Noise trader
f_t	Investment sentiment Momentum	

Table 1: Theories that establish relationships between fund flows and asset returns both contemporaneous and ex-post. Source: author

Investment sentiment theory is based on investor beliefs on the direction of the market which is reflected in the latest trend. Investors thus behave irrationally as their buy or sell decisions are based on over-or under reactions to past performance and not on changes in fundamentals (Barberis et al., 1998). An optimistic sentiment may drive investors to allocate more money into funds, thus pushing prices up (Remolona et al., 1997).

In connection with the above fund flows can be seen as indicators of investor sentiment since people investing in investment funds are probably the less informed investors in the financial markets (Warther, 1995) and are less confident about their financial decisions (Fortune, 1998). Therefore, investor sentiment and information revelation can be related as those investors who do not possess the information might act upon investor (Alexakis et al. 2004).

Therefore, if investor sentiment is a significant factor in determining market returns, then fund flows – as a proxy of investment sentiment – should correlate with the past performance of the market. Thus, the correlation between fund flows and past returns may be spurious, and a confounding variable could be investor sentiment, that influences both returns and flows.

Another phenomenon that is used to justify the existence of a relationship between fund flows and returns is momentum investing that means buying when the market is rising and selling when it is declining and can also result from over- or under reaction

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of certain new pieces of information (Fortune, 1998). It can have a short occurrence when only the current prices are taken into account or can last for longer time period when the past performance is analysed to make decisions for the future. The first may be detected by a correlation between fund flows and stock returns, while the latter through the persistence in returns (Davidson and Dutia, 1989).

A fund flow induced change in the demand for securities causes trading and consequently affects security prices. The positive contemporaneous relationship is supported by the price pressure hypothesis documented in Boyer and Zheng (2002).

Information revelation is another theorem that explains a relationship between contemporaneous returns and ex-post flows. The market moves as trading reveals information; this induces further trading that translates into price changes (Boyer and Zeng, 2002). As investors respond to new information they reallocate resources accordingly, thereby fund flows will move in one direction and that will affect market returns (Warther, 1995).

Furthermore, the phenomenon of noise trading is strongly related with information revelation. Noise traders base their investment decisions on a whim rather than information. They may mislead less sophisticated investors into thinking that their trading is a sign to buy, creating further upward pressure on prices (Fortune, 1998).

In a recent paper, Jotikasthira et al. (2011) documents the causality between asset returns and the push or pull effects originating from the investor base. When fund managers receive fund inflows they are bound to spend the excess liquidity which entail creating demand and thus pushing up asset prices. Money outflows, on the contrary, mean asset sales of investment funds that result in the fall of the asset prices.

Many studies examined fund flows using the micro approach, however the first paper that analysed aggregate fund flows was written by Warther (1995). He examined the relationship between returns fund flows, and fund that aggregate security are highly correlated with concurrent unexpected funds flows, but unrelated to concurrent

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expected flows. Warther also found evidence of a positive relation between flows and subsequent returns and evidence of a negative relation between returns and subsequent flows.

Remelona et al. (1997) investigate the effect of market returns on fund flows by identifying instrumental variables that influence returns but are not affected by flows. These variables include capacity utilisation, CPI, domestic employment rate and the Federal Reserve's target federal funds rate. All of these macroeconomic indicators impact returns but are independent of flows. Then returns are decomposed into a part caused by the variables and a part explained by fund flows. Their findings show that short- term returns do not affect fund flows.

Fortune (1998) furthered Warther's examination of the causality between market performance and fund flows. Based on data spanning 1984-1997 he finds that security returns do affect future fund flows, and that some fund flows do affect future security returns. But he finds no persistence in security returns. Shocks, for instance, to stock returns do not imply further changes in returns, which means rationale for momentum trading over long periods is not bolstered.

Boyer and Zheng (2002) explore the same relationship but differentiate between flow to different investment sectors, namely mutual funds, pension funds and foreign investors. They assumed that the relationship between fund flows and returns is different for individual and institutional investors; moreover, this relationship can also differ by institution type depending on their investor base, incentives and regulations. They prove that for mutual funds, pension funds and foreign investors the positive relationship between returns and stocks is a result of price pressure. This paper examined the US market.

Froot et al. (2001) included international fund flows in their analysis. Their work included US funds investing in 44 foreign countries covering both developed and emerging markets including the Czech Republic, Poland and Hungary. Their results support the idea that returns are a good predictor of future flows for all examined region. However, the fund flows' predictive power on future returns proved

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significant only in the case of emerging markets. Their explanation for this was that international investors updated their forecasts more frequently and possessed private information on the market. This contradicts the theory that fund investors are less sophisticated. In the developed markets flows were not good predictor of security returns.

A few papers deal with non-US markets. This comes naturally, since the investment fund market has the longest history in the United States, where the first trust was established in 1887 (Chatfield-Roberts, 2006). Thus long time series are available and the data is relatively stable. Alexakis et al. (2004) for instance, examines the dynamics between stock returns and fund flows in the Greek market. They took a similar approach to Fortune (1998), however, they tested for a bi-causal relationship between stock returns and fund flows. They found that bi-causality exists for lagged returns. Their explanation was that in Greece there is a minimum requirement for stock allocation in the case of equity funds. Cash inflows to equity funds reduce the proportion of equity below the regulatory minimum, and thus, managers have to purchase stocks to compliant again. Thus, inflows cause an increase share prices.

Bengtsson (2009) examined aggregate European fund flows and market performance in developed markets from 2000 to 2008 using quarterly data obtained from EFAMA. For relative return calculation, Morgan Stanley Capital International (MSCI), Dow Jones global and European indices were used. The paper does not support the hypothesis that fund flows affect subsequent returns nor that return affect future flows. They conclude that investment fund flows do not seem to contribute financial instability by inflating or deflating stock market prices. However, their data shows both contemporaneous and lagged correlation between fund flows and stock market returns.

Some of the literature presented above has concluded that fund flows might have a predictive power over the market returns. If it is true, fund flow data can be a useful tool in developing different trading strategies. Moreover, information on fund flows can be used when making asset- regional and sector allocation decisions.

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A study commissioned by Deutsche Bank published by Meyer et al., (2006) indicates that professionals are on the outlook for the importance of fund flows. The research tested different hypothetical trading strategies that involved data on fund flows. First they tested the strategy based on the direction of weekly fund flows in the same week. According to the strategy, a short position should be taken on the benchmark index if the fund flows are negative and a long position if the fund flows are positive. The strategy outperformed the market; however in reality replication of this strategy is not possible as fund flow data are not available at the time of decision making. Second, they modified their strategy by using fund flow data from the previous week. The results of the lagged week strategy were not satisfactory, nor did other variations outperform the market. Finally, Meyer et al. came up with a measure of liquidity momentum a measure of rising contracting liquidity. Flows might be still positive but with a declining amount of inflows and can be still negative with a smaller and smaller outflow amounts suggesting a declining or rising investor conviction. Liquidity pulse compares the current fund flow size with the average size of the flow from the last three weeks. High liquidity pulse is a result of consequent inflows for a longer period; therefore, it means expansion and as a consequence results in higher performance in the respective region. The trading strategies based on the liquidity pulse are a combination of the direction of the one week flow, the direction of the four week average flow and the liquidity pulse. The first version considers a strong/weak liquidity pulse as a contra indicator. Negative signal is when the liquidity pulse is above 1 and between 0 and -1, while a positive signal when it is below -1 and between 0 and 1. The strategy outperformed the market however, failed to provide enough of signals for trading.

Another study commissioned by Commerz Bank in 2010 conducted by Meyer analysed the possibility of using fund flow data obtained from EPFR in asset allocation decisions. When making their asset allocations decisions, investors apply a scoring system that allows them to rank the possible investment opportunities according to some criteria. The aim of the study was to find out whether adding fund flow data to the ranking criteria would improve the investors' decision-making

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model. In order to reduce volatility, they used four-week average flows as a percentage of the total AUM. First, fund flow data was applied in regional equity allocation decisions, computing a score for fund flows and reallocating the assets across regions based on the changes in the score. This strategy outperformed the equally weighted benchmark portfolio. The next approach reallocated only between developed and emerging equity markets, investing in that market which showed the highest inflows or lowest outflows or both. This strategy resulted in higher returns compared to the equally weighted portfolio. Finally, the use of fund flows in asset allocation decisions between different asset classes was also examined. When the strategy based on fund flow data was applied for equity versus bond allocations also it proved to be more successful than the benchmark strategy. Thus it can be concluded that using fund flow data creates added value when applied in asset allocation decisions.

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6. Empirical Research

6.1. Data on Analyst Forecasts

6.1.1. Dataset

The database collected for the empirical research of my dissertation is truly unique. The source of the data on analysts' forecasts was Bloomberg. The database includes 7 countries that are part of the EMEA region, which is an abbreviation for Europe, Middle East and Africa. My focus area within EMEA region is on Austria, Czech Republic, Poland, Hungary, Romania, Russia and Turkey, which I will collectively refer to as Emerging Europe. The table below summarises the data at hand.

Country	**Index Code**	**Stocks**	**Aggregate weight of stocks in index**	**Number of stocks**
Austria	ATX	Telekom Austria, Verbund, Vienna Insurance Group, Wienerbeger, Erste Bank Group, Andritz, Immofinanz, OMV, Raiffeisen Bank International AG, Voestalpine.	80.84%	10
Czech Republic	PX	CEZ, Kommercni Banka, New World Resources, Telefonica, Unipetrol.	59.73%	5
Poland	WIG	Bank Pekao SA, KGHM Polska Miedz SA, PGE SA, Polski Koncern Naftowy Orlen S.A., Polskie Gornictwo Naftowe i Gazownictwo SA, Powszechna Kasa Oszczednosci Bank Polski SA, Powszechny Zaklad Ubezpieczen SA, Tauron Polska Energia SA, Telekomunikacja Polska SA.	55.25%	9
Hungary	BUX	MOL, Magyar Telekom, OTP Bank, Gedeon Richter.	94.09%	4
Russia	Micex	Gazprom, Lukoil OAO, Norilsk Nickel, Novatek, Rosneft, Rostelekom, Sberbank, Surgutneftegas, Tatneft, Uralkali, VTBBank.	82.04%	11
Romania	BET	Banca Transilvania, BRD-Groupe Societe Generale, Petrom, SC Fondul Proprietatea SA.	81.73%	4
Turkey	ISE	Akbank TAS, Anadolu Efes Biracilik Ve Malt Sanayii AS, BIM Birlesik Magazalar AS, Haci Omer Sabanci Holding	64.66%	12

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		AS, KOC Holding AS, Tupras Turkiye Petrol Rafinerileri AS, Turk Telekomunikasyon AS, Turkiye Garanti Bankasi AS, Turkiye Halk Bankasi AS, Turkiye Is Bankasi, Turkiye Vakiflar Bankasi Tao, Yapi ve Kredi Bankasi AS.		

Table 2: Summary of Data on Analyst Forecasts. Source: author.

I use the primary stock market index from the 7 countries, and I gathered the blue chip stocks that make up 55-95% of the respective indices. The aggregate weights of the stock in my examination universe differ according to the concentration of the given market. The aim was to include stock to have a minimum 50% representation of the index. Another arbitrary criterion was to include stocks that are covered by at least 5 analysts to insure reliable dispersion measurement.

I included stocks in their primary listing market and excluded ADRs (American Depository Receipts) traded on another market. For instance, two Austrian stocks, Erste Bank Group and Vienna Insurance Group are both traded in Vienna, and are included in the ATX. Their ADRs are traded in Prague, and make up 35% of PX.

For each stock, I gathered all published equity research by all brokerages from 1st January, 2000- 25th March, 2012. This data is not sorted and published in a manner that allows for direct download, probably because users of this information do not search for historical recommendations. For each of the 55 stocks in my database, the ANR function in Bloomberg provides the currently valid recommendations, target prices from each analyst. To obtain this data historically, one has to obtain historical analysis from each analyst individually. Data compilation is unstructured in Bloomberg in this respect, as I believe the primary function is to show the currently valid recommendations, and historical data can be obtained only by individually downloading the recommendations for each stock, from each analyst at each date. Ultimately, I obtained 22,568 entries, that cover forecasts from 437 analysts, covering 55 stocks for a period of 13 years. The gathering of this database was the product of tedious work with the aid 3 of my students who wrote their master's thesis under my supervision on this subject. The value in this database also lies in its length, it does encompass a complete economic cycle with booms and busts.

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The number of analyst forecasts for each year is shown in figure 3. I compiled the data during February- March 2012. The number of analyst opinions recorded increases monotonically with the years. This stems from two reasons, one professional the other technical. While databases for developed markets track analyst forecasts back to several decades, emerging markets including EMEA region's coverage is more recent and a reliable collection of data is not available for lengthy periods. The technical limitation is that tracking forecasts historically is limited in Bloomberg. Collection of current analyst forecasts is permitted, and tracking back the analysts' forecasts historically is visible for analysts with current coverage. Forecasts of analysts who no longer cover the stock are practically impossible to discover. This limits the reliability of the data available from the early years (e.g. 2000-2007) and is the typical case of survivorship bias, i.e. only those forecasts are present in the early years whose analysts survived up to date. For future research, I intend to update my database regularly and therefore keep track of all existing forecasts in order to avoid this bias. This will be necessary as long as Bloomberg does not change the structuring of the data retrieval.

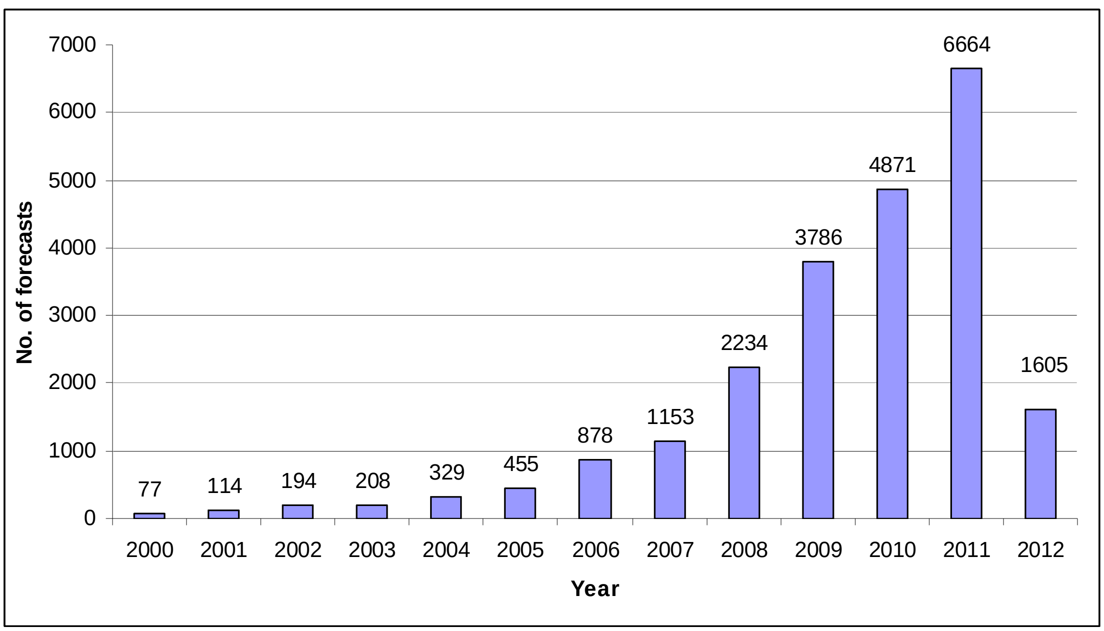

Figure 3: The number of analyst forecasts collected for each year is monotone increasing. Source: author.

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The table below shows an excerpt of the database for analyst forecasts. A data entry includes index, stock, analyst, brokerage, general experience, company specific experience, coverage, recommendation, publication date, target price, forecast period, close price.

1	Index	Firm name	Analyst	Brokerage house	General experience (days)	Firm-specific experience	Coverage	Recommendation	Date	Target Price	Forecast Period	Close Price
2	BUX	MOL	PETER CSASZAR	KBC SECURITIES	105	105	8	hold	2012.02.06	20500	12	20460
3	BUX	MOL	HENRY MORRIS	GOLDMAN SACHS INTL	1577	1577	10	neutral/attractive	2012.02.08	21750	12	20195
4	BUX	MOL	MATTHEW LOFTING	NOMURA INTL PLC	81	81	3	neutral	2012.01.09	21000	12	16770
5	BUX	MOL	LYDIA RAINFORTH	BARCLAYS CAPITAL	3007	2567	18	equalwt/negative	2012.02.06	24500		20460
6	BUX	MOL	ATTILA VAGO	CONCORDE SECURITIES LTD	4830	4818	5	equalweight	2012.01.27	22000		19565
7	BUX	MOL	KONRAD ANUSZKIEWICZ	IPOPEMA SECURITIES SA	1492	800	9	buy	2012.01.18	21900	12	18600
8	BUX	MOL	BRENDAN MICHAEL WARN	JEFFERIES INTL LTD	1807	135	8	hold	2012.01.20	19000	12	19200
9	BUX	MOL	BRENDAN MICHAEL WARN	JEFFERIES INTL LTD	1799	127	8	hold	2012.01.12	19000	12	17025
10	BUX	MOL	TAMAS PLETSER	ING BANK NV HUNGARY BRANCH	4649	4391	19	buy	2012.01.27	23000	12	19565
11	BUX	MOL	KENAN NAJAFOV	CITIGROUP GLOBAL MARKETS	1317	0	8	neutral	2012.02.17	20000		19100
12	BUX	MOL	WOJCIECH KOZLOWSKI	ESPIRITO SANTO INVESTMENT	316	0	5	sell	2012.01.24	15194,17		19145
13	BUX	MTELEKOM	ALEXANDER KAZBEGI	RENAISSANCE INVESTMENT MGMT	5470	117	56	buy	2012.02.13	550	12	536
14	BUX	MTELEKOM	ALEXANDER KAZBEGI	RENAISSANCE INVESTMENT MGMT	5449	96	8	buy	2012.01.23	550	12	555
15	BUX	MTELEKOM	ALEXANDER KAZBEGI	RENAISSANCE INVESTMENT MGMT	5438	85	8	buy	2012.01.12	550	12	516
16	BUX	MTELEKOM	PIOTR JANIK	KBC SECURITIES	1804	103	13	sell	2012.02.13	475	12	536
17	BUX	MTELEKOM	VERA SUTEDJA	ERSTE BANK DER OESTERR.SPARI	2152	1751	8	hold	2012.02.02	580	12	546
18	BUX	MTELEKOM	ATTILA GYURCSIK	CONCORDE SECURITIES LTD	2030	2030	8	equalweight	2012.01.03	651		509
19	BUX	MTELEKOM	WALDEMAR STACHOWIAK	IPOPEMA SECURITIES SA	1162	674	11	sell	2012.01.18	450	12	545
20	BUX	MTELEKOM	ALEXANDER BALAKHNIN	GOLDMAN SACHS	2115	814	30	neutral/neutral	2012.01.10	612	12	515
21	BUX	MTELEKOM	ZOLTAN PALFI	CREDIT SUISSE SECURITIES	498	248	10	outperform	2012.02.23	600		586
22	BUX	MTELEKOM	ZOLTAN PALFI	CREDIT SUISSE SECURITIES	455	205	19	outperform	2012.01.11	600		516
23	BUX	MTELEKOM	ZOLTAN PALFI	CREDIT SUISSE SECURITIES	448	198	19	neutral	2012.01.04	500		492
24	BUX	MTELEKOM	JINDRICH SVATEK	RAIFFEISENBANK AS	5124	3615	4	hold	2012.02.03	590	12	547
25	BUX	RICHTER	NATALYA ZAGVOZDINA	RENAISSANCE CAPITAL LTD	3625	84	35	hold	2012.02.15	41350	12	37900
26	BUX	RICHTER	JAMES VANE-TEMPEST	JEFFERIES INTL LTD	677	677	9	hold	2012.02.14	32200	12	38170
27	BUX	RICHTER	JAMES VANE-TEMPEST	JEFFERIES INTL LTD	670	670	10	hold	2012.02.07	34700	12	38605
28	BUX	RICHTER	JAMES VANE-TEMPEST	JEFFERIES INTL LTD	650	650	10	hold	2012.01.18	34700	12	37095
29	BUX	RICHTER	BRAM BURING	WOOD & CO FINL SERVICES	4216	4216	7	hold	2012.02.09	39175	12	38950
30	BUX	RICHTER	VLADIMIRA URBANKOVA	ERSTE GROUP BANK AG	4740	4662	11	buy	2012.02.03	45650	12	38850
31	BUX	RICHTER	ATTILA VAGO	CONCORDE SECURITIES LTD	4849	4208	5	equalweight	2012.02.15	42000		37900
32	BUX	RICHTER	ATTILA VAGO	CONCORDE SECURITIES LTD	4841	4200	8	equalweight	2012.02.07	45854		38605
33	BUX	RICHTER	MAGDALENA KOMARACKA	IPOPEMA SECURITIES SA	1065	405	8	hold	2012.01.18	37100	12	37095

Figure 4: Excerpt of database on analyst forecasts. Source: author.

The database includes the following items:

- Index: the stock market index which the given stock is a component of.
- Stock: the Bloomberg abbreviation for the stock covered.
- Analyst: the name of the analyst publishing the research note.
- Brokerage: the investment firm which the analyst is working for.
- General experience: the time lapse in days between the publication date and the first research note published by the analyst on any stock.
- Company specific experience: the time lapse in days between the publication date and the first research note published by the analyst on the given stock.
- Coverage: the number of stocks covered by the analyst.

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- Recommendation: the qualitative rating of a stock given on an ordinal scale referring to the analysts' advice to purchase, to hold on to or to dispose of the stock.
- Publication date: the date on which research notes are published, i.e. dispersed to clients and data source providers.
- Target price: the estimated fair value of the stock for the forecast period.
- Forecast period: the time horizon for which the forecast is valid. The industry norm is 12 months, in a few rare cases the forecast period was different, e.g. 3, 6, 9 months. These were excluded from the database.
- Close price: the closing price of the stock on the date of publication.

6.1.2. Scales of Measurement

Measurement can be classified into four different scales depending on the data type. Different measurement scales permit different statistical measures of central tendency and dispersion as established by Stevens. (Stevens, 1946 and 1951)

Below is a summary of the scale measurements and the permissible statistics.

Scale Type	Permissible Statistics
Nominal	mode, Chi-squared
Ordinal	median, percentile
Interval	mean, standard deviation, correlation, regression, analysis of variance
Ratio	All statistics permitted for interval scales and the following: geometric mean, harmonic mean, coefficient of variation, logarithms

Table 3: Scales of measurement and permissible statistics based on Stevens (1946, 1951)

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- Nominal scale: data are that equal one another and do not represent any kind of magnitude or order in relation to one another. Typically these include names of characteristics.

- Ordinal scale: data are ordered according to magnitude in a monotonic order, however the relative distances of the observations is not defined. Performance measures that are used in classification as excellent, good, satisfactory are measured on an ordinal scale.

- Interval scale: data is ordered by magnitude with a defined distance measure, enabling quantification of the distance between observations. A familiar example is weather temperature measure in Celsius.

- Ratio scale: in addition to the properties of the interval scale, here the variables have an absolute zero to be referenced to. Most physical measure such as mass, time, length, angle are measured on the ratio scale.

Recommendations are measured on an ordinal scale, as the simplified classification of buy-hold-sell does indeed enable a ranking – the buy recommendation being the most preferable from the company's point of view, followed by the hold and finally the sell recommendation. The distance between a buy recommendation and a hold is none the less undefined in this manner. It is not meaningful to measure by how much is a buy better than a hold. Since our analysis requires a measure of dispersion, I need to think of a way to elevate the measurement scale to at least an interval scale. This may be done using a reference variable such as the upside. The recommendation is derived from the upside, which is measured on the ratio scale, therefore, it is possible to measure recommendations on an interval scale once we apply a scoring system.

Recommendations of analysts vary from a 3 or a 5 step quantitative scale depending on the policy of the brokerage firm. I translate recommendations to numerical scoring. The following table shows the different recommendation scales applied by the different brokerages and the scoring system that is also used by Bloomberg.

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Score					
5	Buy	strong buy	Overweight	market outperform	accumulate
4		neutral/buy	overweight/neutral		
3	Hold	Neutral	Equalweight	market perform	
2		neutral/sell	underweight/neutral		
1	Sell	strong sell	Underweight	market underperform	reduce

Table 4: Scoring system assigned to recommendations to elevate scale of measurement to an interval scale. Source: author.

The target price data are measured on a ratio scale, which allows for all possible statistical measures.

6.1.3. Average return and its dispersion

I proceeded on to grouping data in order to obtain a weekly time-series of forecast mean, and dispersion. I introduce the following notation system.

s – stock where s (1….S) S is the total number of stocks within a country.

a – analyst where a (1….A) A is the total number of analyst in our database.

t – time where t (1…..T)

R – recommendation R (1,2,3,4,5)

$R_{s,t,a}$ is the latest recommendation given for stock s valid on week t by analyst a.

Average of recommendations of a given **stock** on a given week.

$$\frac{\sum_{a=1}^{A} R_{s,t,a}}{A} = R_{s,t}$$

7. Equation

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Dispersion is measured by the standard deviation of recommendations of a given stock on a given week.

$$\sqrt{\frac{\sum_{a}(R_{s,t,a} - R_{s,t})^2}{A}} = \sigma_{s,t}$$

8. Equation

If an analyst does not publish a new recommendation on a given week, I consider the latest recommendation published to be valid up to 3 months time. If no update is given within the next 3 months, I consider the recommendation out of date and exclude it.

The database contained several recommendations by the same analyst for the same stock during the same week. In such cases, I considered the most recent recommendation.

To create country recommendations, I aggregated individual stock recommendations weighting them with their respective weights in the country's main stock index. Index weights are tracked for each month.

$w_{s,t}$ is the weight of the stock in the country index on week t.

I proceed to calculate the average and standard deviation of the country recommendations.

Average recommendation for a given country on a given week:

$$\sum_{s=1}^{S} R_{s,t} \cdot w_{s,t} = R_t$$

9. Equation

Standard deviation of recommendations for a given country on a given week:

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$$\sum_{s=1}^{S} \sigma_{s,t} \cdot w_{s,t} = \sigma_t$$

10. Equation

Now, I have established weekly time series of average opinion represented by the average recommendations, and the heterogeneity of expectations proxied by the standard deviation of recommendation for each of the seven countries of the Emerging European region.

6.2. Data on Investment Fund Flows

The source of fund flow data is the Emerging Portfolio Fund Research (EPFR) database that gathers information from investment funds on their flows globally. It publishes fund flow reports on a daily, weekly and monthly basis and the data are available to subscribers for a fee.

Other data providers in the United States include Investment Company Institute (ICI) (http://www.ici.org). In Europe, the European Fund and Asset Management Association (EFAMA) (http://www.efama.org/index.php) provides quarterly data on fund flows. EFAMA represents the interests of the European investment management industry through member associations with 24 country members and 42 corporate members. However, the most extended database is that of EPFR.

EPFR is a US based company that provides fund flows and asset allocation data to financial institutions around the world. They claim that they track approximately thirty-five thousand, both traditional and alternative funds domiciled globally with USD 16 trillion in total assets. They strive to capture the most of institutional and individual investor flows and fund manager allocations driving global markets. EPFR publishes daily, weekly and monthly equity and fixed income fund flows and monthly fund allocations by country, sector and security. Monthly equity flow data are available from January, 1995 and weekly equity fund data from October, 2000. Their database currently covers 104 emerging and developed markets. They track primarily open-ended funds, however 10% of the funds captured are closed-ended but those

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that allow for monthly or quarterly subscription or redemption. Moreover the funds are not generally exchange traded (ETFs). (Meyer, 2006)

The investor base covered is mainly institutional investors like pension funds and insurance companies who contribute to approximately 70% of the money invested in the funds tracked. (www.epfr.com) These institutional investors invest their money though mutual funds, exchange traded funds, closed-end funds and variable annuity funds/insurance linked funds. This means that the EPFR database is only a subset of all portfolio flows to emerging markets as it covers only institutional investors and not all emerging market destinations of flows. Flows not captured in the EPFR data are investments from hedge funds, proprietary trading desks of foreign brokers and investment banks, foreign insurance companies investing their excess cash and wealthy individuals and individual companies purchasing company stocks for strategic reasons or to invest excess cash. (Miao and Pant, 2012)

The funds that are covered by EPFR are mainly domiciled in developed markets such as Ireland, Luxembourg, United Kingdom, Switzerland, Canada and the United States.

Data tracks the actual country and regional weights, in % terms, of individual funds and average weights by investment manager and Fund Group.

A recent report by IMF also utilises EPFR's high frequency coverage of gross bond and equity flows as an indicator of foreign investors' sentiment to complement the coincident indicator with an even timelier variant to keep up with the need of real time policy calibration. Because of its timeliness and coverage of gross flows, however, EPFR data provides a real time microscope to study foreign investor sentiment. (Miao and Pant, 2012)

According to Meyer (2006) 181 funds were investing in EMEA, mainly domiciled in Luxembourg and Ireland. Approximately 13% of the money invested went to Hungary, 15% was invested in Poland. Most notable is Russia capturing 43% of

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investments and Turkey 9%. Since 2006 the amount of funds tracked was greatly expanded; yet I see this division to be indicative.

EPFR compiles weekly fund flows in US dollars for each mutual fund and publishes the data every Thursday at 5 pm for the prior week Thursday - Wednesday based on the information that was received directly from fund managers or their advisors. This is computed on a country basis as per country and asset allocation details provided by fund managers.

6.2.1. Methodology of Fund Flow Calculation

The methodology of calculating fund flows presented below is based on Meyer (2006). Fund flow data calculation is the residual effect of changes in net asset value, exchange rate changes and value of total fund assets. Define:

A_{t-1}: Total fund assets at the beginning of the week (previous Wednesday market close) in local currency.

A_t: Total fund assets at the end of the week (current Wednesday market close) in local currency.

NAV_{t-1}: Net asset value per share at the beginning of the week in local currency

NAV_t: Net asset value per share at the end of the week in local currency

FX_{t-1}, FX_t, FX avr: Local currency exchange rate against the USD at the beginning, end of the week and the average exchange rate.

Weekly performance of a particular fund is derived from net asset values:

$r_t = (NAV_t - NAV_{t-1}) / NAV_{t-1}$

where r_t is the weekly return or NAV performance in local currency.

This shows price changes in the underlying assets per one share of the investment fund.

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Weekly portfolio change and fund flow is then computed in local currency. Total asset change results from price changes of assets the fund invested in, and fund in- and out-flows coming from new share sales or redemptions.

I first work out portfolio change to arrive to the amount of fund flows. The portfolio change is the performance of net asset value per share multiplied by the total assets at the beginning of the week. Formally, portfolio change is defined as:

$\Delta \Pi_t = r_t \cdot A_{t-1}$

Fund flows in local currency = $A_t - A_{t-1} - \Delta \Pi_t$

All EPFR data are in USD. Therefore, I convert the local currency denomination using the foreign exchange rates. Assets (t-1) are converted using the corresponding exchange rate at the beginning of the week; assets (t) are converted with end of week exchange rates, and finally, the average rates are used for the portfolio change and the fund flow. To illustrate this, I reproduce the numerical example following Meyer (2006).

Assets (t-1) (million euros)	Assets (t) (million euros)	FX (t-1)	FX (t)	FX avr	Weekly fund performance
600	650	1.3	1.34	1.32	5%

Table 5: Sample investment fund's weekly performance. Source: author.

The value of portfolio change is

$\Delta \Pi_t$ = EUR 600mn x 5% = EUR 30mn

Fund flow = EUR 650mn – EUR 600mn – EUR 30mn = EUR 20mn

Total assets increased by 50 million euros, 30 million attributable to capital gains, and 20 million to net fund inflow. Now, I convert this amount into USD, matching beginning and end of week FX rates to the assets.

Asset_{t-1} = EUR 600mn · 1.3 EUR/USD = USD 780mn

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$Asset_t$ = EUR 650mn · 1.34 EUR/USD = USD 871mn

$\Delta \Pi_t$ = EUR 30mn · 1.32 EUR/USD = USD 39.6mn

Fund flow = EUR 20mn · 1.32 EUR/USD = USD 26.4mn

If the exchange rate had remained unchanged, then the Assets (t) would have been the same as the sum of Assets (t-1), Fund Flow and portfolio change. In this example, the USD depreciated against the Euro, resulting in a

The expected value of Assets EoW will differ from the actual value.

$E[Assets_t]$ = USD 780mn – USD 39.6mn – USD 26.4mn = USD 714mn

$E[Assets_t] - Assets_t$ = USD 714mn – USD 871mn = USD –157mn

The difference between the expected assets (t) and the actual assets (t), USD 157mn, resulted from the depreciation in the USD against the EUR during the week and translates into an FX gain for the fund.

6.2.2. The Fund Flows

The fund flow data gathered during my research work are for the same seven countries included in the analyst forecast database, namely Austria, Czech Republic, Hungary, Poland, Romania, Russia and Turkey – collectively called Emerging Europe. The data covers weekly fund flows for equity investment from 27th October, 2000 to 10th August, 2011 that makes up a time-series of 564 observations for each country. Also, I have data for assets under management (AUM) for each week.

The comparison of flow data across countries faces two problems. One is that the countries differ in the magnitude of assets and the volume of the flows. Another problem is that compilation of data by EPFR expanded as years passed by, and currently the dataset covers more funds than at initiation. Therefore, for analysis purposes, I will compute flows in relative terms as a percentage of total assets under management. This will normalise the data to allow for comparisons of countries that

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have different flow sizes and will also handle the problem of the extension of coverage through time.

Also, as the data are denominated in USD, changes in flows will reflect not only investor behaviour, but also the effects of foreign exchange rate fluctuations.

My database includes all funds and country-dedicated funds. All funds include full coverage of EPFR funds and take the pro-rata share of a fund's investments into a country, based on the disclosure of the fund manager. Country-dedicated funds are a sub-set of the all funds data. They include flow from funds only dedicated to investing to a particular country. For analysis purposes, I will use the all funds data to capture the more extended set of fund data.

Estimated country flows (USD mn, all fund types, source: EPFR)

	Austria-Equity	Czech Republic-Equity	Hungary-Equity	Poland-Equity	Romania-Equity	Russia-Equity	Turkey-Equity
10-Aug-11	-62,9	-36,2	-31,2	-118,1	-4,3	-894,6	-175,3
3-Aug-11	-32,9	-3,7	-4,3	-15,1	-0,5	-123,0	-25,9
27-Jul-11	-6,5	-0,7	0,8	1,0	0,1	-17,1	2,9
20-Jul-11	-20,2	-13,5	-13,6	-85,0	-2,3	-259,1	-41,5
13-Jul-11	-5,4	5,9	5,4	7,3	0,3	-4,1	14,9
6-Jul-11	19,8	3,9	3,5	17,6	0,3	66,4	19,5
29-Jun-11	-12,9	-1,9	-2,0	-9,3	-0,9	-196,8	-55,1
22-Jun-11	-18,3	-6,1	-6,9	-27,0	-2,1	-365,3	-29,8
15-Jun-11	-17,9	-7,8	-6,1	-13,0	-0,6	-37,4	-38,1
8-Jun-11	2,9	-8,9	-8,0	-20,5	-1,4	-94,5	-18,8
1-Jun-11	-11,9	-3,2	-3,6	-9,0	-1,2	-62,2	-13,8
25-May-11	-10,5	-13,0	-10,0	-16,5	-1,8	-394,6	-90,7
18-May-11	2,8	-9,3	-6,8	-22,6	-1,2	-453,9	-49,2
11-May-11	-3,2	-4,0	-1,4	5,5	-0,4	-79,6	66,0
4-May-11	11,1	2,7	7,1	43,8	0,8	196,9	26,2
27-Apr-11	-4,1	4,8	3,7	15,5	0,4	299,0	27,4
20-Apr-11	-7,0	-2,9	-2,5	15,1	-0,5	78,4	78,4
13-Apr-11	-13,4	16,0	11,7	112,5	1,4	440,2	117,6
6-Apr-11	-12,0	28,5	28,0	80,7	3,4	838,1	197,0
30-Mar-11	1,0	23,5	18,7	60,6	2,7	841,1	69,7
23-Mar-11	-27,8	-12,1	-10,7	-34,2	-1,6	124,4	-60,7
16-Mar-11	-21,2	-8,4	-8,5	-28,2	-1,4	-225,6	18,6
9-Mar-11	-22,7	-5,7	-4,3	-19,7	-0,5	424,6	-5,6
2-Mar-11	-2,2	-10,8	-8,7	-19,3	-0,7	-3,7	-50,2
23-Feb-11	7,4	1,6	3,0	20,9	0,7	152,5	-33,3
16-Feb-11	14,1	-7,8	-7,1	-20,5	-1,0	-15,7	-106,7
9-Feb-11	-9,6	-2,4	-2,6	4,3	0,1	197,5	-240,4
2-Feb-11	3,6	-20,4	-18,6	-41,2	-2,5	-168,9	-199,8
26-Jan-11	4,3	-7,3	-6,1	-4,3	-0,8	12,8	-104,8
19-Jan-11	26,7	-1,8	-2,1	-14,6	-0,3	740,7	29,7
12-Jan-11	39,7	2,9	2,9	8,1	0,4	202,1	32,6
5-Jan-11	42,1	7,9	7,2	24,6	1,0	237,8	34,0
29-Dec-10	-11,7	1,9	2,2	5,5	0,3	193,9	-28,5
22-Dec-10	-15,3	6,1	8,4	27,9	0,7	195,9	3,6
15-Dec-10	6,5	4,4	7,5	16,6	0,7	216,0	49,2

Estimated country allocations (USD mn, all fund types, source: EPFR)

	Austria-Equity	Czech Republic-Equity	Hungary-Equity	Poland-Equity
10-Aug-11	4 876	2 846	2 282	7 685
3-Aug-11	5 564	3 337	2 680	9 076
27-Jul-11	5 814	3 455	2 772	9 398
20-Jul-11	5 266	3 491	2 819	9 267
13-Jul-11	5 293	3 517	2 842	9 392
6-Jul-11	5 442	3 555	2 867	9 494
29-Jun-11	5 299	3 482	2 799	9 277
22-Jun-11	4 921	3 626	2 462	8 422
15-Jun-11	4 897	3 659	2 494	8 534
8-Jun-11	5 032	3 741	2 547	8 711
1-Jun-11	5 107	3 766	2 565	8 756
25-May-11	4 984	3 645	2 483	8 476
18-May-11	5 644	3 707	2 589	8 372
11-May-11	5 685	3 769	2 637	8 538
4-May-11	5 804	3 848	2 685	8 713
27-Apr-11	5 759	3 878	2 709	8 779
20-Apr-11	5 911	3 580	2 938	8 600
13-Apr-11	5 868	3 567	2 932	8 574
6-Apr-11	5 919	3 584	2 948	8 525
30-Mar-11	5 790	3 413	2 803	8 101
23-Mar-11	5 820	3 389	2 700	7 988
16-Mar-11	5 560	3 286	2 625	7 750
9-Mar-11	5 913	3 427	2 736	8 090
2-Mar-11	5 938	3 373	2 685	7 948
23-Feb-11	6 554	2 707	2 063	7 594
16-Feb-11	6 632	2 743	2 089	7 679
9-Feb-11	6 600	2 776	2 112	7 775
2-Feb-11	6 580	2 817	2 147	7 872
26-Jan-11	6 452	2 827	2 162	7 880
19-Jan-11	6 064	2 973	2 293	7 608
12-Jan-11	5 920	2 945	2 279	7 545
5-Jan-11	5 831	2 915	2 259	7 464
29-Dec-10	5 794	2 862	2 212	7 321
22-Dec-10	5 976	2 902	3 001	7 747
15-Dec-10	5 932	2 884	2 980	7 700

Figure 5: Excerpt of fund flow dataset. Source: author.

6.3. Data on Equity Market Returns

Market returns for equities in my analysis universe were downloaded from Bloomberg. Daily closing prices downloaded in both local currency and in USD. Weekly returns were calculated from Thursday close price to the next week's Wednesday closing value. This was important to ensure congruence with the fund

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flow data. Moreover the Morgan Stanley Capital International Indexes (MSCI) were downloaded as well in both local currencies and USD terms.

6.4. Hypotheses and Methodology

In this chapter, I present my hypotheses and the results of the empirical tests I conducted with the aim of identifying possible relationships and causality between analyst opinion, fund flows and market returns. As shown in figure 6, a relationship may exist between any of the three variables.

My proposition is that the functioning and compensation of the equity research industry indicates that the market does reimburse their efforts, subsequently assigns an economical value to their information-processing work. From this stems my assumption that market efficiency in its strongest form does not hold in practice and that the semi-strong form would not hold without the existence of equity research.

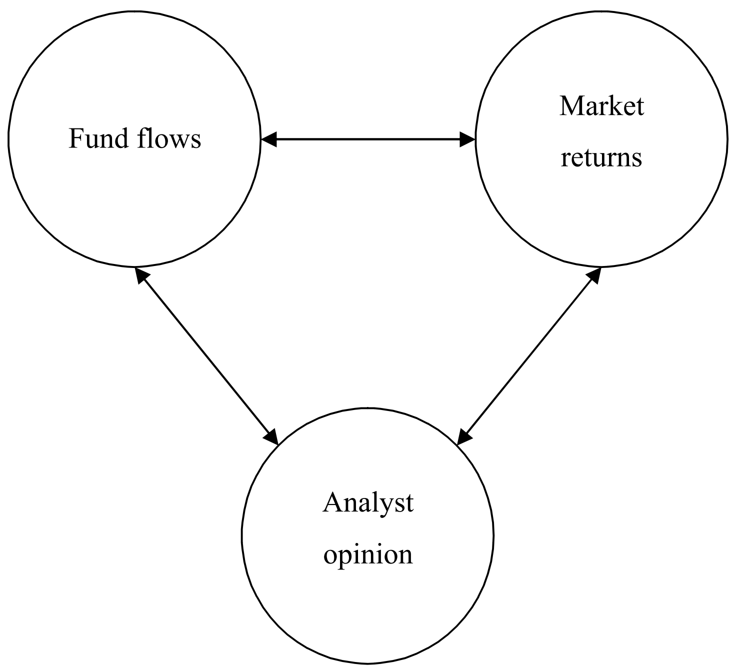

Figure 6: The inter-relations between analyst forecasts, investment fund flows and market returns. Source: author.

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Organising Data

One problem with the data is that the **observations are not equidistant**, which means that the target prices are all issued on different dates (non-uniform publication date) and therefore refer to different dates (non-uniform target dates). This makes comparison between target prices issued by different analysts problematic. To circumvent this problem, I assume that the issued target price is valid, until a new one is published by the analyst. In practice, target prices become outdated before a new target price is issued. This, however, cannot be measured objectively as it is a function of market sentiment and market conditions, thus my simplifying assumption will suffice academic purposes. Once I assume target prices to be valid for more than one day, I will be able to obtain weekly data of all valid target prices by the different analysts for a given stock. From this a mean and a standard deviation may be computed.

Before embarking on any analysis, the dataset require careful testing for meeting the **usual statistical requirements** of independence, normality of the distribution, and whether the process is stationary. For most of my calculations, I use Excel and Eviews statistical software.

The time-series and abbreviations:

Index returns:

Average weekly returns were computed in both local currency (LC) and in USD. Notation:

e.g. ATX(LC) refers to the average return of the ATX index in local currency.

Analysts:

Average and median of recommendation (R) and target price (TP) of analysts for a given country index.

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Standard deviation of recommendation (R) and target price (TP) of analysts for a given country index.

Fund flows:

The ratio of net fund flows to assets under management (FF/AUM).

Methodology of using Granger Causality

Co-movement and correlation does not automatically imply causality. Several variables in the economy and in nature have been observed to correlate but are by no means in a causal relationship.

Granger (1969) sought to present a solution to examine whether a variable *x* causes another variable *y* by capturing how much of *y* in time *t* can be explained by past values of *y* and then augmenting the regression by adding lagged values of *x* in hope of improving the explanation. *y* is said to Granger-cause *x* if past values of *y* improve the explanatory power to predict *x*, i.e. if the coefficients on the lagged *y*'s are significantly different from zero. A two-way causation may frequently be present; thus *x* Granger causes *y* and *y* Granger causes *x*.

Eviews has a tool to calculate Granger causality. The statement that "*x* Granger-causes *y*" does not mean that *y* is the effect or the result of *x*. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term.

Also, finding a suitable lag length, l, should be done in a manner that corresponds to reasonable beliefs about the longest time over which one of the variables could help predict the other. Lags are indicated in the index. Examination up to 8 weeks lag was carried out; the choice of 8 lags was based on tests showing no significant increase in explanatory power of lags beyond the 8th lag.

Eviews runs bivariate regression of the form:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \cdots + \beta_l y_{-l} + u_t$$

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for all possible pairs of (x, y) series in the group. The reported F-statistics are the Wald statistics for the joint hypothesis:

$$\beta_1 = \beta_2 = \cdots = \beta_l = 0$$

for each equation. The null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression.

The Granger causality test requires the time-series to be stationary. To achieve this, I used the Augmented Dicky-Fuller test (ADF) to test for the existence of a unit root. If the null-hypothesis for the existence of a unit root is rejected, then the time series is considered stationary. Otherwise, the first differential is tested. If it is also non-stationary, the second differential is taken, and so forth. Once the time series become stationary, the Granger cause test may be applied. I found that all the time-series were stationary without any alteration. Therefore, the causality tests can now follow.

H1: A relationship exists between index returns and average analyst opinion (recommendation and target prices).

Average target price for BET (1,2,5 lags), BUX (1,2 lags), ISE (3-8 lags) and Micex (1-4 lags) indices Granger-caused USD-based returns negatively.

This means that higher target prices for Romanian, Hungarian, Turkish and Russian stocks 1-3 weeks earlier led to lower dollar returns.

Average recommendations for ATX (1 lag) Granger-caused local currency and dollar-based returns negatively. Conversely, average recommendations for BET (2,5,6,7,8 lags) and BUX (2 lags) Granger-caused local currency returns positively.

This means that average recommendations gave mixed results regarding the direction of the relationship, with significant causality for the Austrian (1 lag), Romanian (2,5,6,7,8 lags) and Hungarian (2 lags) indices.

One might infer that target prices prove to be a more consistent indicator to analyst opinion, and have a more straightforward effect on average returns, albeit in a negative direction, whereas past recommendations provide ambiguous signals in predicting weekly returns.

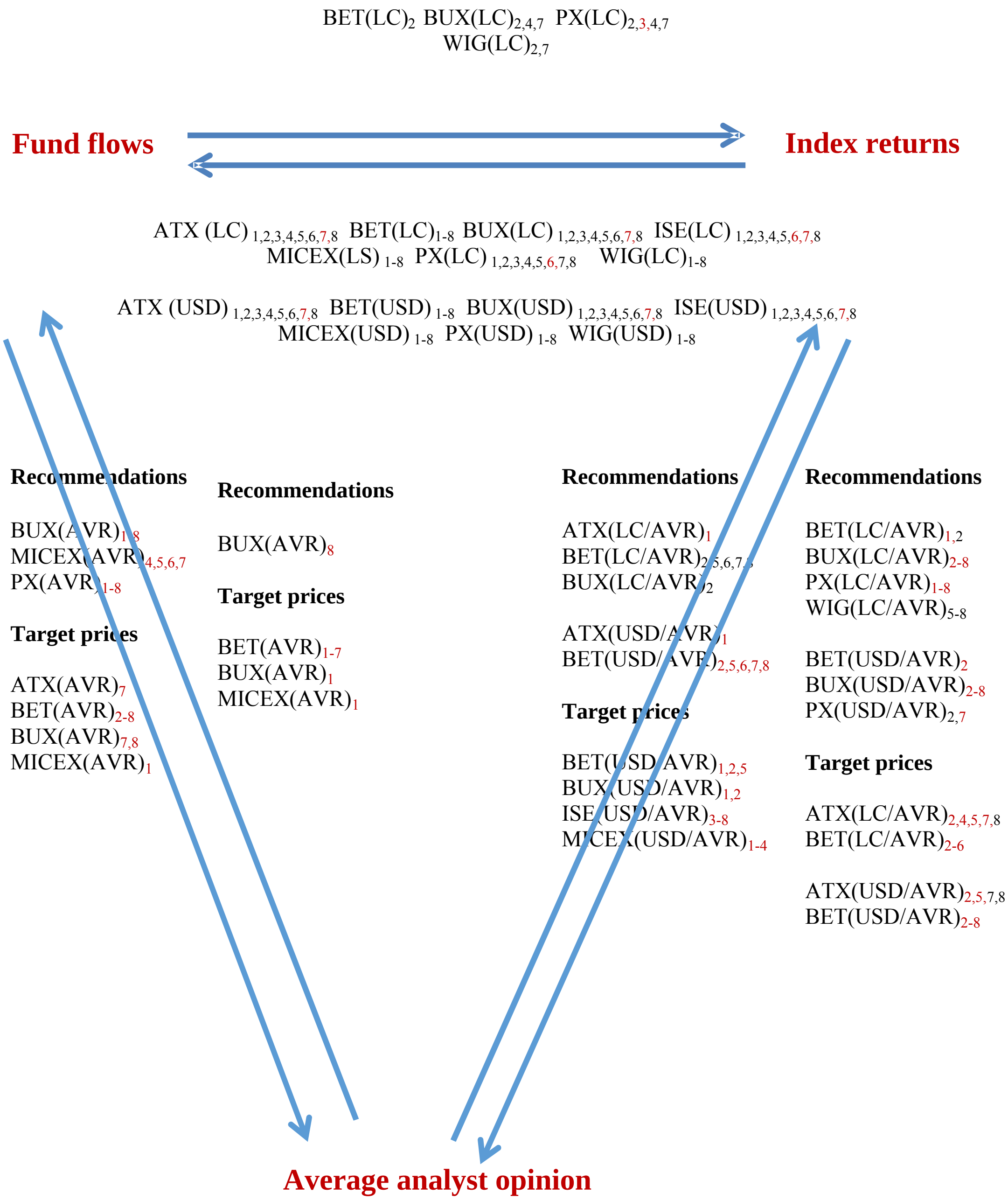

Figure 7: Full period Granger-causality for given markets with specified lags. Numbers in red indicate a negative relationship; the others indicate a positive relationship.

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To further explore this effect, I repeated the same test on two parts of the data, the first covered the period from 25th September, 2006 to 14th September, 2008, a period of economic boom, when stock markets saw an upward trend. This period I called the pre-crisis period.

The second, the post-crisis period covers the period from 14th September, 2008 to 8th August, 2011. 15th September, 2008 was the day chosen to divide the data into pre- and post-crisis is the memorable day when Lehman Brothers announced filing for bankruptcy; its share price fell 90% on that trading day.

In the pre-crisis period, average target prices for ATX (1 lag), BUX (1,2,6 lags) and ISE (2-8 lags) Granger-caused local currency returns negatively. Average target price for ISE (1,2,7,8 lags) Granger-caused USD-based returns negatively.

Recommendations proved less effective in explaining index returns in the pre-crisis period. Only BET (7,8 lags) Granger-caused local currency returns negatively. BET (7 lags) showed significant causal relationship with USD-based returns, and median recommendation for ISE (2 lags) showed significant causation for USD-based returns.

The post-crisis period better reflected the importance of analyst opinion is causing index returns, albeit the relationship is a negative one. Average target prices for ATX (2,7,8 lags), BET (1,2,3,5,6 lags), BUX (1,2,4,5 lags), ISE (3-8 lags), Micex (1,2,3,4,5,7 lags) Granger-caused local currency returns negatively. Also, average target prices for ATX (2 lags), BET (1-3 lags), BUX (1-5 lags), ISE (3-8 lags), Micex (1-3 lags) Granger-caused USD-based returns negatively for the post-crisis period.

The impact of recommendations was less apparent in the post-crisis period, but corroborated previous results with two examples of causation. Average recommendation for ATX (1,2 lags) and BET (2,3 lags) Granger-caused local currency returns negatively; furthermore ATX (1 lag) and BET (2,3 lags) Granger-caused USD-based returns negatively.

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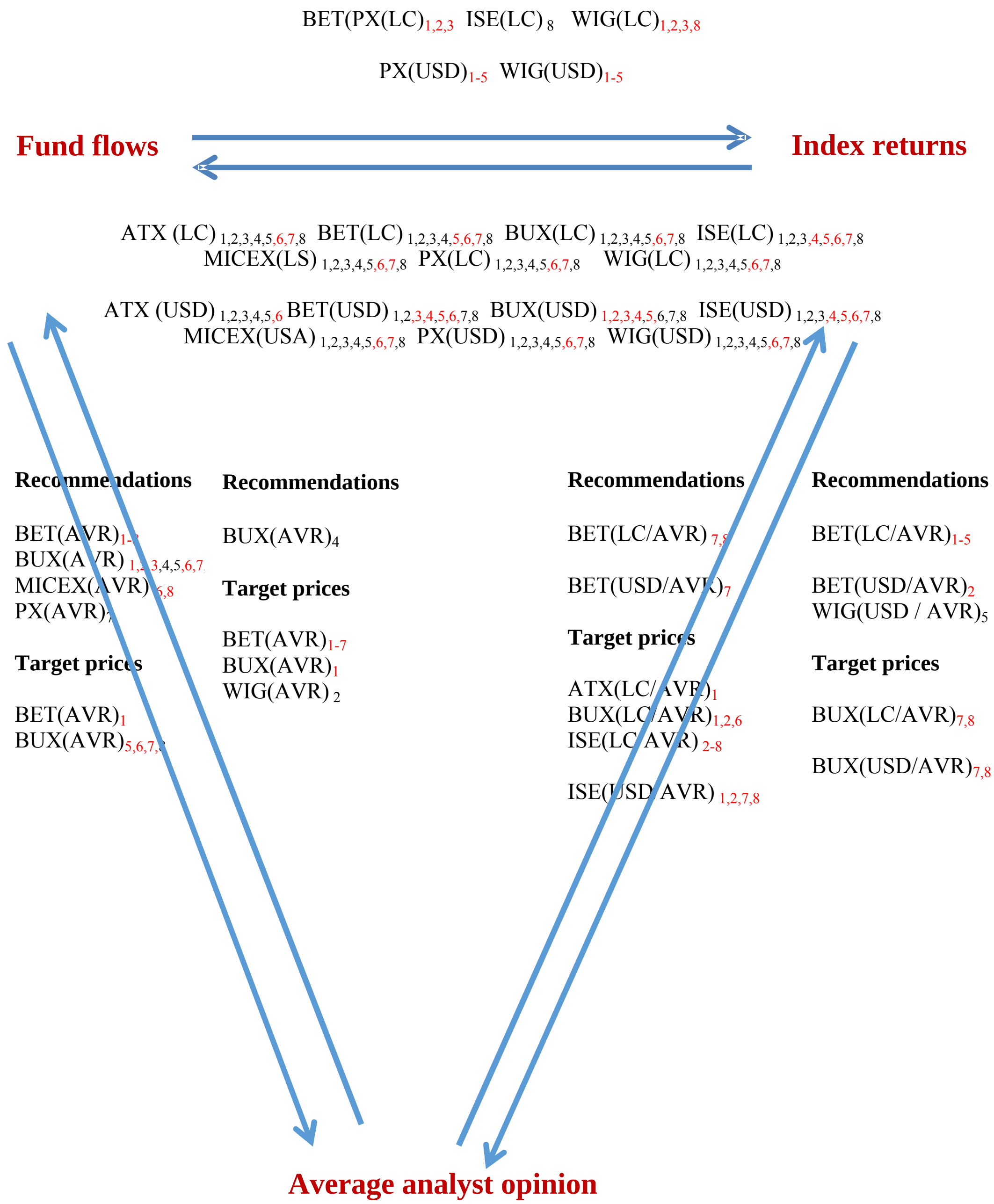

Figure 8: Pre-crisis period Granger-causality for given markets with specified lags. Numbers in red indicate a negative relationship; the others indicate a positive relationship.

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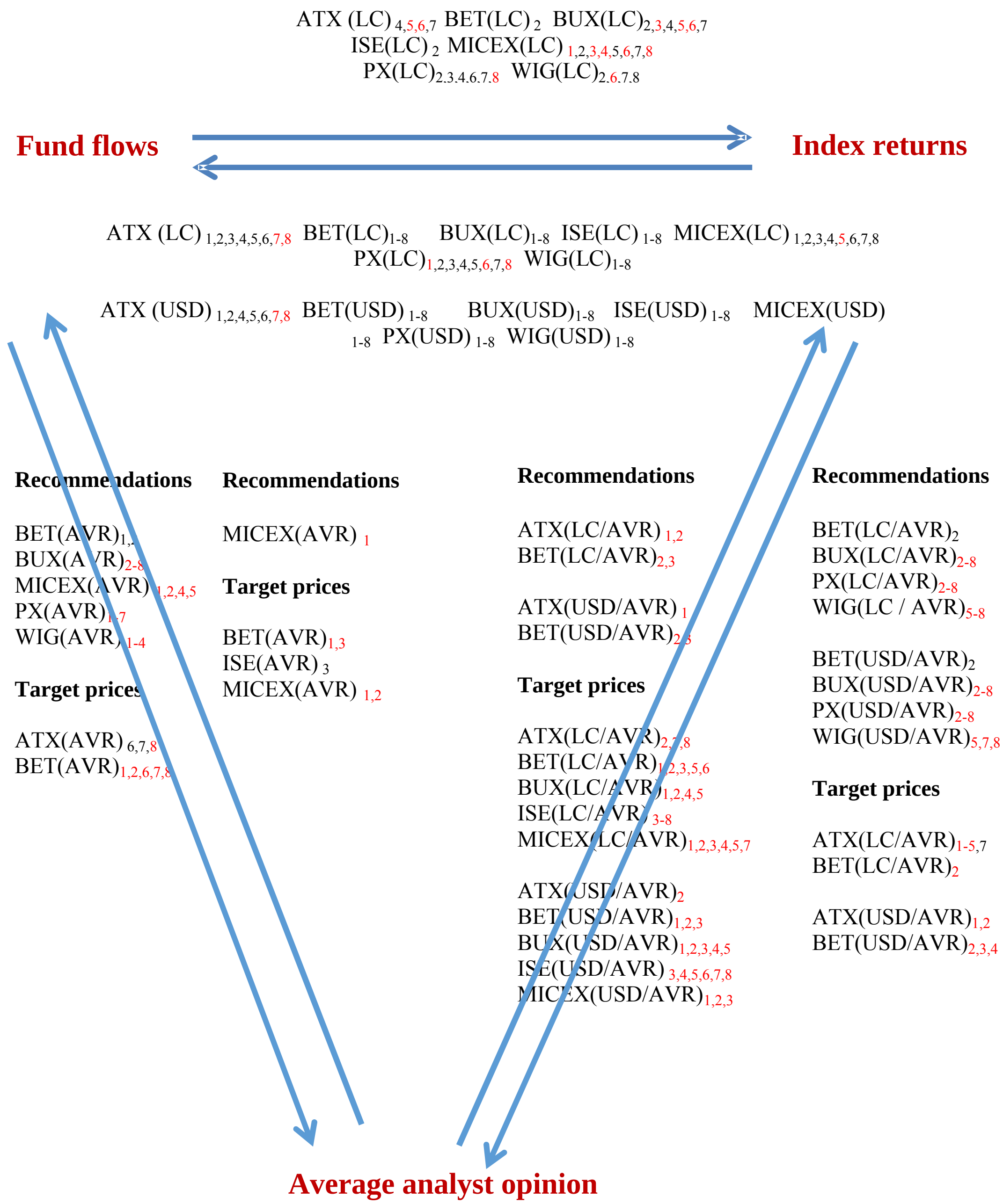

Figure 9: Post-crisis period Granger-causality for given markets with specified lags. Numbers in red indicate a negative relationship; the others indicate a positive relationship.

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Results from splitting the time-series into bull (pre-crisis) and bear (post-crisis) markets supported the findings from the examination of the full period, namely, that average target prices cause weekly returns negatively.

The causal relationship in the opposite direction was also tested to get proof whether index returns caused analyst opinion. Examining the full period, average target prices for ATX (2,4,5,7 lags) and BET (2-6 lags) Granger-caused local currency returns negatively. Also, ATX (2,5 lags) and BET (2-8 lags) Grangers-caused USD-returns negatively.

For the same period, average recommendations showed mixed results. BET (1 lag), BUX (2-8 lags) and PX (5-8 lags) Granger-caused local currency returns negatively. Also, average recommendations for BET (2 lags) and BUX (2-8 lags) Granger-caused USD-based returns negatively. On the other hand, BET (2 lags) and WIG (5-8 lags) Granger-caused local currency returns positively. Also, average recommendations for PX (2 lags) Granger-caused USD-based returns positively.

Pre-crisis average target prices barely showed any effect, only BUX (7, 8 lags) Granger-caused both local currency and USD-based returns negatively.

Average recommendations in the bull market showed similarly rare instances of causality. Average recommendation for BET (1-5 lags) Granger-caused local currency returns negatively, and average recommendations for BET (2 lags) Granger-caused USD-based returns negatively. The WIG (5 lags) showed a positive relationship, on the other hand.

In the bear market, average target prices for ATX (1-5 lags) and BET (2 lags) Granger-caused local currency returns negatively, and ATX (1, 2 lags) and BET (2, 3, 4 lags) Granger-caused USD-based returns negatively.

Average recommendations for BUX (2-8 lags), PX (2-8 lags) and WIG (5-8 lags) indices negatively Granger-caused local currency returns, and BUX (2-8 lags), PX (2-8 lags) and WIG (5, 7, 8 lags) also negatively Granger-caused USD-based returns.

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BET index returns behaved in a positive directions, lag 2 impacted both local currency and USD-based returns positively.

Results from the causality tests between analyst opinion and index returns generally shows a negative relationship – especially in the post-crisis period – target prices appear to give the message to trade the opposite of what analyst recommend. A possible explanation could be that analysts appear to be late in publishing their opinion, or another explanation could be that the market does not react to their opinion in the first 8 weeks following publication; after all, analysts publish 12 month target prices and recommendations.

H2: A relationship exists between the dispersion of analyst opinion (target prices and recommendations) and market returns.

Dispersion is captured by **relative standard deviation** of all valid target prices and recommendations issued for a given stock during a given week. **Weekly market returns** are calculated for each stock individually in both **local currency and USD** as in the previous examinations. To test whether a **causal relationship exists**, and to determine its direction, I will use the **Granger** causality test between the two time-series for each stock.

Dispersion of target prices for the full period for ISE (1,2 lags) and Micex (2,7 lags) negatively Granger-cause local currency return, and ISE (1-5,7 lags) and Micex (2, 4 lags) negatively Granger-cause USD-based returns. This is in line with evidence reported in the literature showing a negative relationship between dispersion and returns, indicating that higher dispersion is a proxy for risk, and therefore result in lower returns. Uncertainty is a different concept from risk. Bélyácz (2010) summarises and explains the literature that defines risk as having known or estimated probabilities, whereas uncertainty considers both the outcomes and their probabilities as unknown. Investors require compensation for holding stocks that entail high uncertainty, as measured by the high dispersion in analyst forecasts. The opinion of analysts that show in one direction, or have a low dispersion means that analysts are more certain regarding the future prospects of the stock.

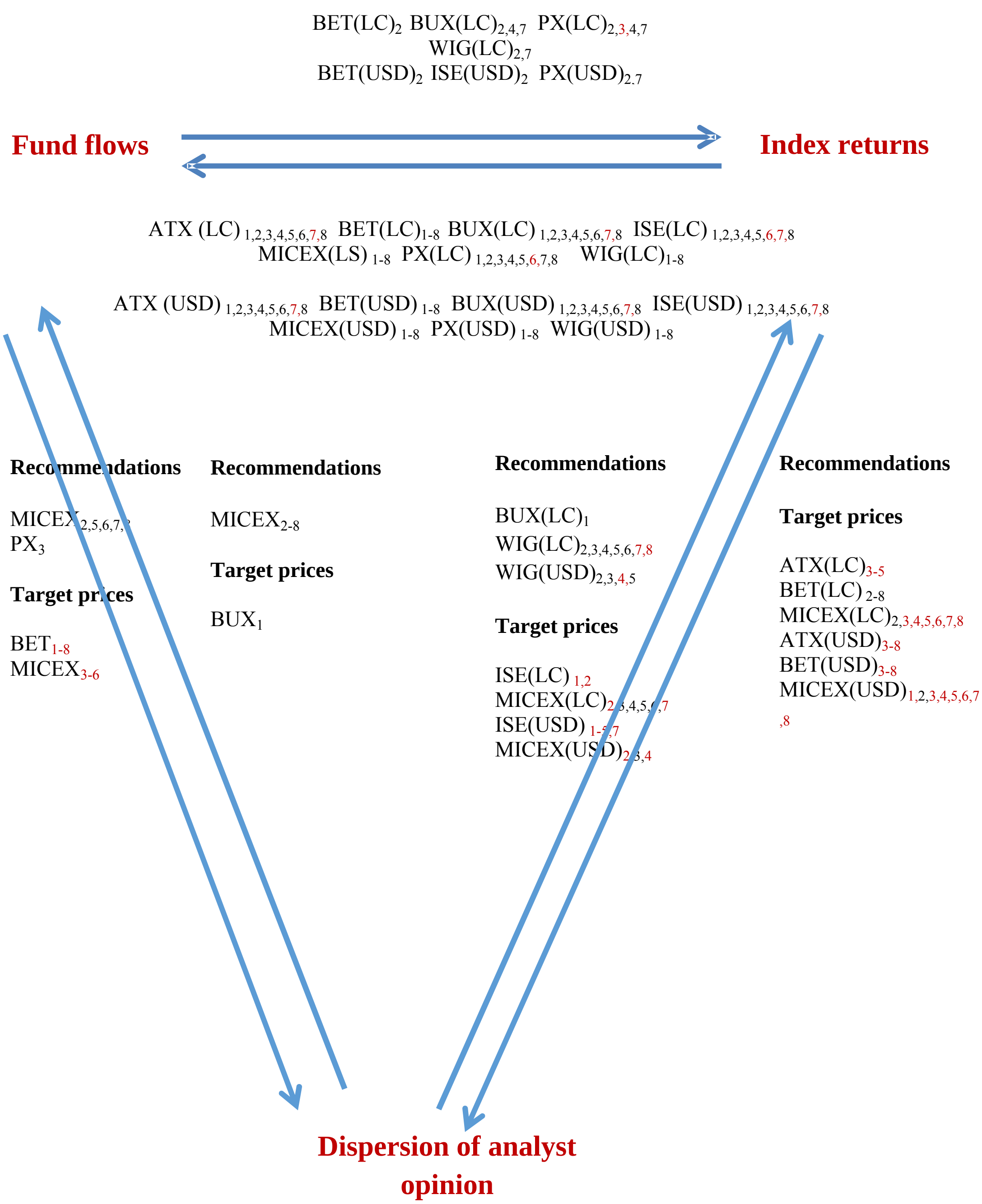

Figure 10: Full period Granger-causality for given markets with specified lags. Numbers in red indicate a negative relationship; the others indicate a positive relationship.

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The results are only true in the case of two markets, the Turkish and the Russian, and the latter showed mixed results. The outlier result is the positive causal relationship from Micex (3-6 lags) for local currency returns.

Looking at the pre-crisis period, the dispersion of target prices for ATX (1-3 lags), ISE (1 lag) and Micex (3 lags) Granger-caused USD-based returns negatively; in line with the literature results. The post-crisis period showed that dispersion of target prices for ATX (7,8 lags) positively Granger-caused local currency and USD-based returns, whereas ISE (1-3 lags) negatively caused USD-based returns.

Dispersion of recommendations showed the opposite results. For the full period, BUX (1 lag) and WIG (2-6 lags) positively caused local currency returns, with the exception of WIG (7,8 lags) where the causal relationship was positive. The pre-crisis period confirmed the positive causal relationship for PX (1 lag) and WIG (2-5 lags) for local currency returns and for PX (1 lag) and WIG (1-5 lags) impacting USD-based returns. A minor outlier was WIG (1 lag) with a negative relationship with local currency returns. The post crisis period also gave proof of positive causation for BUX (1-4 lags) and WIG (3-5 lags) for local currency returns. Outlier considering the direction of the relationship was PX (2 lag) that showed a significant negative relationship with local currency returns.

These result, although mostly show positive direction of causality, are mixed and would be insufficient to draw conclusions, but the difference in the direction of the impact recommendation and target price dispersion has on returns is noteworthy. As if, one is a strong signal to investors, whereas the other is being published under pressure to please.

The effect of returns on analyst opinion was explored. Local currency returns for ATX (3-5 lags) and Micex (3-8 lags), and USD-based returns of ATX (3-8 lags), BET (3-8 lags) and Micex (1,3-8 lags) negatively Granger-caused dispersion of target price. Outliers could also be spotted: Local currency returns causal relationship with BET (2-8 lags) and Micex (2 lags) dispersion of target prices showed a positive relationship.

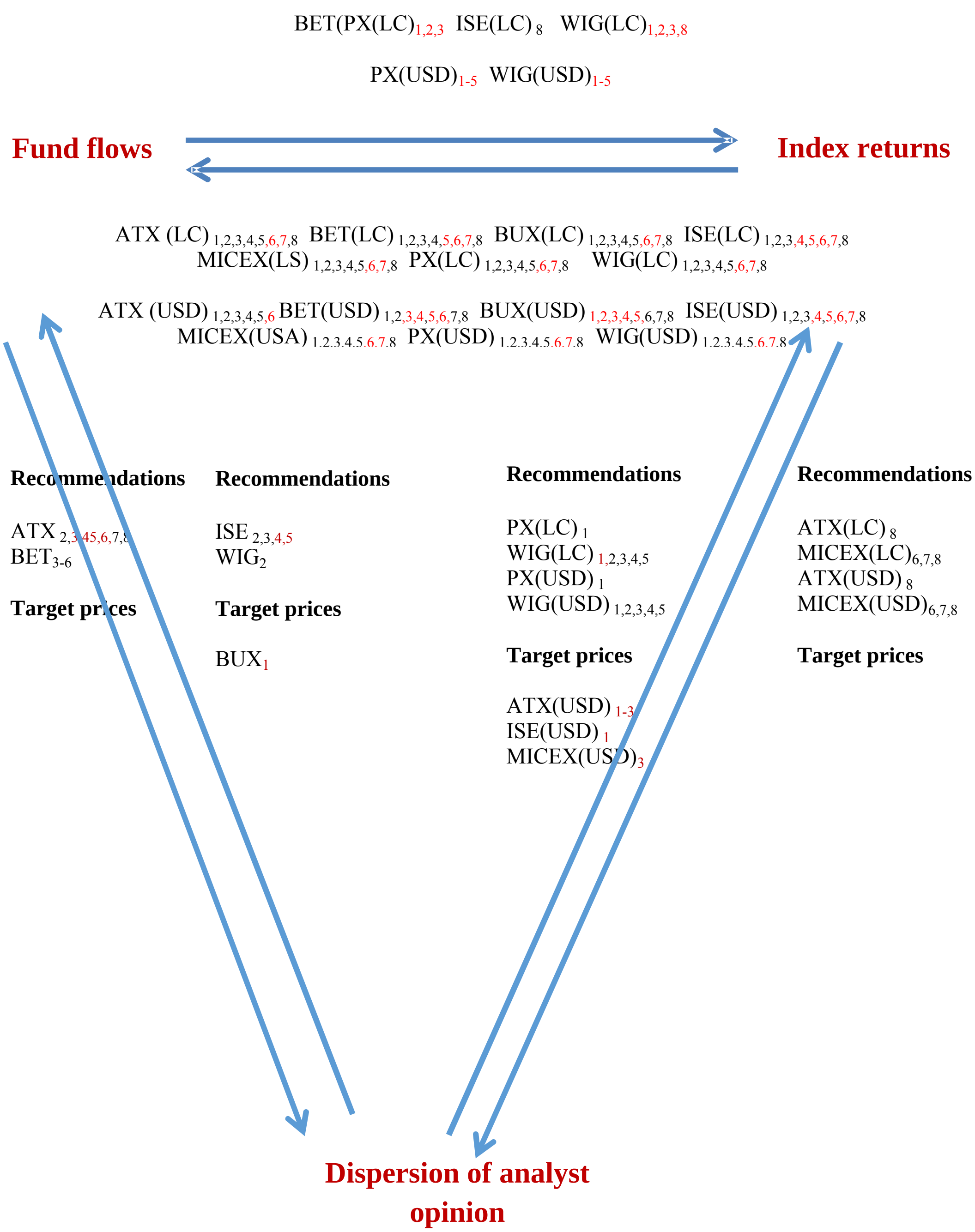

Figure 11: Pre-crisis period Granger-causality for given markets with specified lags. Numbers in red indicate a negative relationship; the others indicate a positive relationship.

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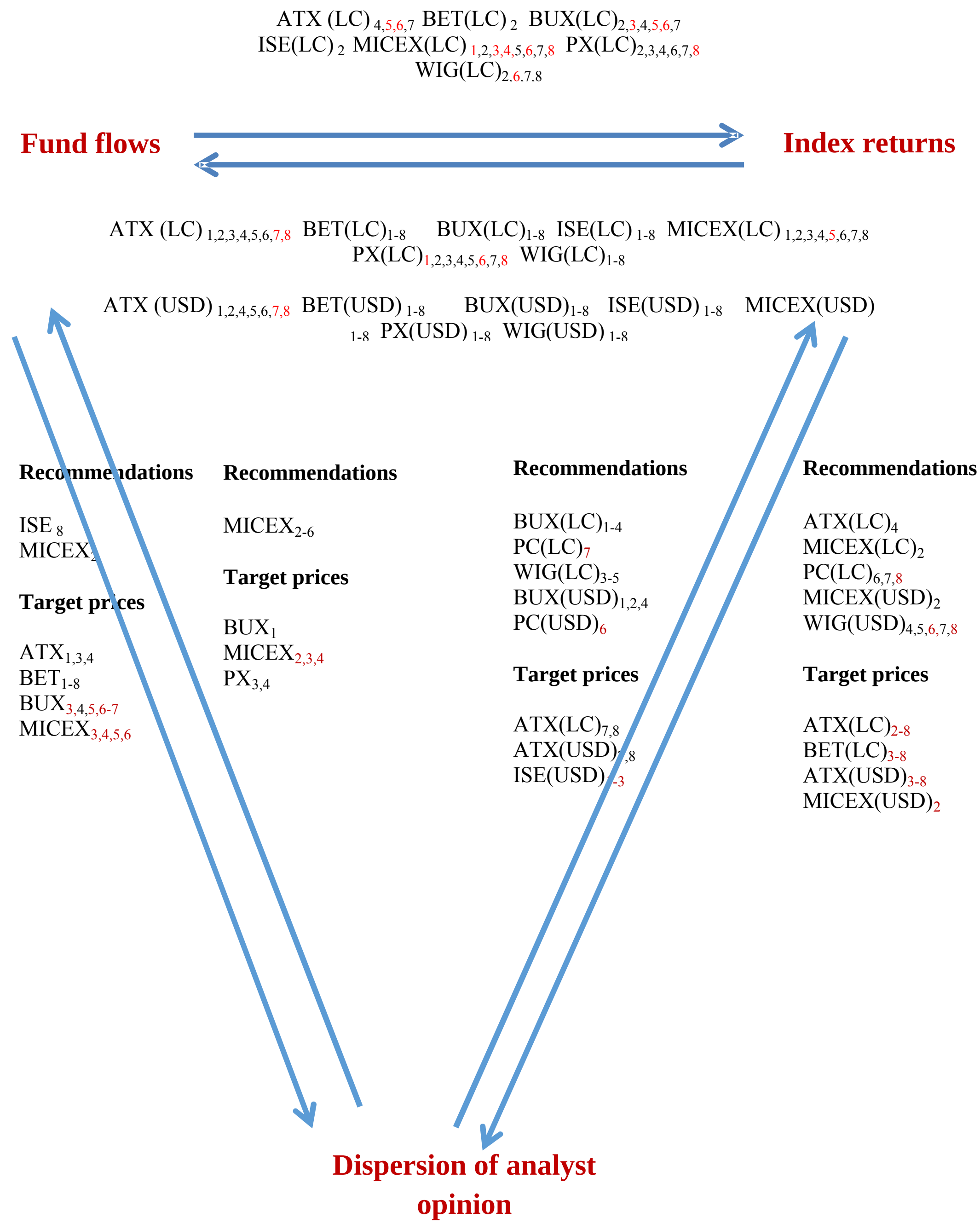

Figure 12: Post-crisis period Granger-causality for given markets with specified lags. Numbers in red indicate a negative relationship; the others indicate a positive relationship.

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No effect was observed for the pre-crisis period. The post-crisis period showed that local currency returns Granger-caused ATX (2-8 lags) and BET (3-8 lags) negatively, as expected. Also, USD-based returns Granger-caused ATX (3-8 lags) and Micex (2 lags) negatively.

There was no effect of index returns on the dispersion of recommendations, however, the sub-periods showed surprising results. For the pre-crisis period, local currency and USD-based returns for ATX (8 lags) and Micex (6-8 lags) Granger-caused the dispersion of analyst recommendations positively, as if to mean, that higher returns before the crisis were a source of greater confusion among analysts. The post-crisis period showed positive causal relationship between local currency returns for ATX (4 lags), Micex (2 lags), PX (6,7 lags), also USD returns for Micex (2 lags) and WIG (4,5,7 lags). Though, results came in mixed with a negative causal relationship at PX (8 lags), and USD returns versus WIG (6,8 lags).

The other part of my research refers to investment fund flow data. The compilation, publication of the data, its reporting and monitoring by investors implies that investment fund flow data carry economic value that is not yet fully understood by the market. To unveil the effects of this data, I examined its relationship with market returns.

H3: A relationship exists between investment fund flows and market returns.

Flow data were arranged on a weekly basis, published to include data from every week's Thursday to the following week's Wednesday. The weekly stock returns were constructed accordingly to cover a Thursday-Wednesday period. The reason I had arranged analyst forecast data in the same weekly format in which fund flows are reported is to allow for testing the two datasets against one another. Fund flows (FF) are taken as a percentage of assets under management (AUM) of the funds covered and hereinafter referred to commonly as the funds, whereby I refer to (FF/AUM).

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The hypothesis is that a positive relationship exists between index returns and FF/AUM, and the causal relationship can be in both directions. The results support the hypothesis.

For the full period tested, funds Granger-caused local currency and USD-based returns for BET (2 lags), BUX (2,4,7 lags), PX (2,4,7 lags) and WIG (2,7 lags) positively.

The surprising results comes from the pre-crisis period, funds negatively cause returns. In the case of PX (1,2,3 lags) and WIG (1,2,3,8 lags) a negative Granger-causality was recorded for local currency returns. Also, PX (1-5 lags) and WIG (1-5 lags) also negatively Granger-caused USD-based returns. An outlier was ISE (8 lag) that positively affected local currency returns. The post-crisis period mixed results. ATX (4,7 lags), BET (2 lags), BUX (2,4,7 lags), ISE (2 lags), Micex (2,5,7 lags), PX (2-7 lags) and WIG (2,7,8 lags) showed positive relationships with local currency returns, whereas ATX (5,6 lags), BUX (3,5,6 lags, Micex (1,3,4,6,8 lags), PX (8 lags) and WIG (6 lags) showed negative relationships with local currency returns. A similarly mixed result was arrived at for USD-based returns.

These results could be interpreted that funds impacted returns during and after the crisis, and had inconsistent mixed effects in the earlier stage, perhaps owing to the fact that data collected from the funds did not cover a considerable proportion of the trading volume on CEE equities. However, post-crisis results show that fund data could be valuable for those who trade based on observing the positive causality of funds on index returns.

The second part of the question is how do index returns help understand funds. The assumption again is that the relationship is positive. For the full period, local currency and USD-based returns significantly Granger-cause funds positively for ATX (1-6,8 lags), BET (1-8 lags), BUX (1-6,8 lags), ISE (1-5,8 lags), Micex (1-8 lags), PX (1-5,7,8 lags) and WIG (1-8 lags). Results are fully in line with our expectation. Higher returns induce higher fund flows. Pre-crisis period shows this positive causal relationship for all indices for 1-3 lags. Some alternate relationship directions are

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shown for later lags, but this does not affect our conclusion, that positive (negative) returns for the past 1-3 weeks cause higher (lower) fund flows. The post-crisis period also corroborates this result and conclusion, and shows a strong causal relationship for all indices covering all lags. Slight outlying results (visible in the graph) do not impact the overall conclusion.

H4: A relationship exists between average analyst opinion (target prices and recommendations) and investment fund flows.

Average target prices for BET (1-7 lags), BUX (1 lag) and Micex (1 lag) Granger-cause funds negatively for the full period.

In the pre-crisis period, BET (1-7 lags) and BUX (1 lag) indices show a negative causal relationship (expect WIG (2 lags) shows a positive relationship). Post-crisis, BET (1,3 lags) and Micex (1,2 lags) support the negative relationships established for the previous periods. Again, an outlier here is ISE (3 lags).

Average recommendations have a less apparent impact. For the full period, only BUX (8 lags) shows any significant causal relationship with funds, and that is a negative relationship. During the pre-crisis period, BUX (4 lags) shows a positive relationship, and the post-crisis period brings Micex (1 lag) to cause funds in a negative directions. These results are weak and do not help in explaining how funds react to analyst opinion.

The other direction of causality was tested with more apparent results. Funds Granger-caused average analyst opinion (target prices and recommendations). For the full period examined, ATX (7 lags), BET (2-8 lags), BUX (7,8 lags) and Micex (1 lag) proved to be significant causality contributors in a negative direction.

Pre-crisis BET (1 lag) and BUX (5,6,7 lags) and post crisis ATX (8 lags) and BET (1,2,6,7,8 lags) where examples of funds negatively causing analyst average target prices.

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As for recommendations, funds for the full period showed that BUX (1-8 lags), Micex (4-7 lags) and PX (1-8 lags) negatively cause average recommendations. This was corroborated by results from BET (1-8 lags), BUX (1,2,3,6,7,8 lags) and Micex (6,8 lags) for the pre-crisis period. Also, funds significantly Granger-caused average analyst recommendations for BUX (2-8 lags), Micex (1,2,4,5 lags), PX (1-7 lags) and WIG (1-4 lags) for the post crisis period.

H5: A relationship exists between the dispersion in analyst opinion (target prices and recommendations) and investment fund flows.

The dispersion in analyst target prices for the fully period included only BUX (1 lag) to positively Granger-cause funds. In the pre-crisis period, BUX (1 lag) had a negative effect, and in the post-crisis period, BUX (1 lag) and PX (3,4 lags) Granger-caused funds positively, whereas Micex (2,3,4 lags) Granger-caused funds negatively. These mixed results shows that no causal effect could be spotted on the data examined.

The dispersion in analyst recommendations positively caused funds. For the full period, Micex (2-8 lags) showed significant Granger-causality, in the pre-crisis period ISE (2,3 lags) and WIG (2 lags) supported the same positive causal relationship. An odd results was ISE (4,5 lags) showing a negative relationship. In the post-crisis period, Micex (2-6 lags) also positively Granger-caused funds.

The results are somewhat contradictory (odds exist) and results apply only to one or two indices, none the less, it is interesting to look to the explanation of a positive relationship; why does higher dispersion in recommendations cause more fund inflow. Either investors are risk-lovers and buy on ambiguity; or do not interpret dispersion of opinion as a proxy of risk. Another possible explanation could be that high dispersion reflects contrarian opinion which is a strategy investors in the Russian, Turkish and Polish markets may have followed.

Examining whether funds impact the dispersion of analyst opinion, I find that the relationship in negative when looking at the full period. Funds negatively Granger-

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caused dispersion of target prices for BET (1-8 lags) and Micex (3-6 lags). No significant causality was uncovered in the bull market of the pre-crisis period, but the bear market in the post-crisis period showed mixed results. For BUX (3,5,6,7 lags) and Micex (3,4,5,6 lags) a negative causal relationship was shown, whereas ATX (1,3,4 lags), BET (1-8 lags) and BUX (4 lags) showed a positive causal relationship.

Funds negatively Granger-caused dispersion of analyst recommendations for Micex (2,5,6,7,8 lags) and PX (3 lags) for the full period; ATX (2,7,8 lags) and BET (3-6 lags) for the pre-crisis period; and ISE (8 lags) and Micex (2 lags) for the post-crisis period. Again odds results came from ATX (3,4,5,6 lags) where a negative relationship was recorded.

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7. Summary

In this dissertation I investigated equity market efficiency in Emerging Europe through the relationship between sell-side equity analyst forecasts, fund flow data and market returns. The financial literature has examined the effect of both analyst forecasts and fund flows separately, in order to better understand what impacts market returns. No literature, to my knowledge, captured the equity market microstructure (analyst forecasts, market returns, and fund flows) in one framework. This enables me to examine whether the causal relationships between the two factors and returns could also be derived from the third relationship: namely, between analyst forecasts and fund flows. The argument in support of my approach is that the product of analysts' work serves clients at investment funds; therefore I assume that empirical tests would prove a causal relationship between what analysts say and what investment fund managers act upon. The counter argument could be the time mismatch in the investment horizons: analyst forecast offers a 12 month view, whereas investment funds make both shorter term (daily and weekly) investment decisions in addition to the mid-term and long-term ones (monthly and annual).

According to Fama (1970) markets are efficient to the extent that new information is reflected in asset prices. How does new information get priced-in? The equity market micro-structure reveals that analysts analyse new information and present their research to investors, who in turn may act upon the new information. In an efficient market, where the efficient market hypothesis holds in its stronger form, analyst forecasts would have an immediate effect on fund flows, that in turn have an immediate effect on market returns; both effects taking place instantaneously, and no further impact should be observed.

The empirical results of my dissertation contradicts the efficient market hypothesis, since in many cases market returns significantly over- and under-reacted to analyst forecasts. This can be explained in different ways. Firstly, I am examining emerging markets, therefore temporary inefficiencies can be considered as normal. Secondly, as information is priced in slowly, I observed two-directional relationships which

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indicate that it is difficult to determine whether analyst forecasts or fund flows drive equity returns or vice versa.

The database used in my empirical research covers the equity market of 7 emerging European countries (Austria, Czech Republic, Hungary, Poland, Romania, Russia, and Turkey) from 1st January 2000 – 25th March 2012. This period spans the economic crisis of 2008; therefore I refer to the period before Lehman Brothers' collapse on 15th September 2008 as the pre-crisis period, and consequently the latter period is called as post-crisis period.

The fund flow data is the proprietary data of EPFR that publishes weekly data on each Friday covering the previous week's net amount of money flows into a country's equity market, covering both country dedicated funds as well as all funds allocated to that country. EPFR data are quite expensive, and it is only available to paying clients.

The data on analyst forecast are unique and original since I compiled all items one by one from Bloomberg's database covering 437 stocks, and 55 sell-side equity analyst target prices and recommendations (jointly referred to as analyst forecast), a total of 22,568 entries. Weekly average and dispersion of target prices and recommendations were set up for each country, with 631 weeks examined.

The datasets on fund flows, analyst forecast and market returns are all aligned in weekly format to enable time-series analysis.

My findings can be summarised in three points:

1. Fund flows

In general, fund flows and market returns have a positive two-directional relationship. This is in line with my initial expectations, which is also supported by empirical literature including Fortune (1998), Goetzmann and Massa (1999), Ippolito (1992) and Alexakis et al. (2004). Positive fund flow means liquidity influx to the market that will hike asset prices, and hence returns. Conversely, higher returns attract money into funds, through cross-asset reallocations.

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My findings show that fund flows Granger cause market returns for the subsequent 2 weeks. However, this was evident only in 4 countries and the results vary during the pre- and post-crisis period. Before the crisis, the relationship is rather negative, and post-crisis I record rather positive relationships. Therefore, the direction of the relationship is uncertain and fairly unstable in time. Hence, during some periods, fund flows may help in forecasting market returns, nevertheless, a profitable trading strategy can hardly be based solely upon this dataset.

At the same time, the reverse effect of market returns on fund flows is much stronger, covers longer lags and was proved in the example of most countries. The positive relationship is more apparent in the post-crisis period. One possible explanation could be that before the crisis, the database comprised much less funds than in the later periods and EPFR's database coverage of funds expanded continuously.

2. Average analyst forecasts

I observed a negative relationship between average analyst target prices and subsequent returns. High average target prices Granger-caused lower returns after 1-3 weeks. The same results were seen when the Granger-causality test was repeated for the pre- and the post-crisis periods separately, with the most apparent results for the post-crisis period. This surprising result signals that during this period, analysts were not successful in forecasting equity returns. A possible explanation could be that higher target prices attract sellers to the market who see an opportunity to realise gains. Or high target prices in the Emerging European equity research arena could have been a signal for a contrarian trading strategy.

For recommendations, the relationship is also negative, but results are less robust than in the case of target prices.

When examining the relationship between average analyst forecasts and fund flows, I also arrive at surprising results. Namely, average analyst forecasts negatively Granger caused subsequent fund flows. There is no literature on this relationship, but my initial assumption was that analyst forecasts Granger cause fund flows in a positive

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direction. A possible explanation to the negative relationship can be an immediate over-reaction to analyst forecasts and slow corrections in the following 1-2 weeks. The reverse relationship, whether fund flows affect analyst forecasts were not significant on this sample.

3. Dispersion of analyst forecasts

The dispersion of analyst target prices and market returns show a negative relationship in both directions. My results contradict Malkiel (1982), and Barry and Brown (1985) and therefore, I cannot consider dispersion as a possible proxy for risk, as they have suggested. On the other hand, my results were inline and support the findings of the mainstream literature such as Diether, Malloy, and Scherbina (2002) and Johnson (2004). However, the results are unstable across countries and through time, especially following the crisis. The explanation provided by literature (see McNichols and O'Brien (1997) Denis and Dimitri (2002), and (Chen et al., 2001)), could also be considered for my data. First reason is the costly short selling in Emerging Markets, and later on, complete short selling ban during the post-crisis period. Another reason is that prices suffered upward bias more, as negative information was withheld from the market, coupled with low market breadth.

The empirical tests confirmed the negative direction causal relationship for target prices, but found a positive causality for recommendations. The same results were confirmed for the pre-crisis period. However, the crisis period failed to show any meaningful direction for causality as results were mixed, which means that dispersion of forecasts was misleading during the crisis.

The relationship between the dispersion of analyst target prices and fund flows is less pronounced, but shows a negative relationship in the subsequent 1-2 weeks. My presumptions were not reflected in my results. I assume that the information transmission mechanism between analyst forecast and fund flow data is subtle, and therefore the tests failed to capture it.

I summarise the results of the empirical tests in figure 13. In the first column, the hypotheses state a causal relationship and its direction between any two variables. The second column indicates whether analyst forecast is captured by target price (TP) or recommendation (Rec.). The last three columns show whether the relationship was positive or negative, and for how many subsequent weeks (lags) was the relationship significant. Results are shown when the relationship is not mixed and holds for at least 2 countries.

		Full period	Pre-crisis (bull)	Post-crisis (bear)
H1 Average forecasts → Market returns	Rec.	pos (1-2 lags)	0	neg (1-3 lags)
	TP	neg (1-3 lags)	neg (1-2 lags)	neg (1-3 lags)
H1 Market returns → Average forecasts	Rec.	neg (1,2 lags)	0	neg (2-8 lags)
	TP	neg (2-5 lags)	0	neg (1-2 lags)
H2 Dispersion of forecasts → Market returns	Rec.	pos (1-2 lags)	pos (1 lag)	0
	TP	neg (1-2 lags)	neg (1-3 lags)	0
H2 Market returns → Dispersion of forecasts	Rec.	0	pos (6-8 lags)	pos (4,5 lags)
	TP	neg (3-8 lags)	0	neg (2-8 lags)
H3 Fund flows →Market returns	n.a.	pos (2 lags)	neg (1-3 lags)	pos (2 lags)
H3 Market returns → Fund flows	n.a.	pos (1-4 lags)	pos (1-3 lags)	pos (1-3 lags)
H4 Average forecasts → Fund flows	Rec.	0	0	0
	TP	neg (1 lag)	neg (1 lag)	0
H4 Fund flows → Average forecasts	Rec.	neg (1-8 lag)	neg (1-8 lag)	neg (1-5 lag)
	TP	neg (7,8 lag)	neg (1,5 lag)	0
H5 Dispersion of forecasts → Fund flows	Rec.	0	pos (2-3 lags)	0
	TP	0	0	0
H5 Fund flows → Dispersion of forecasts	Rec.	pos (2,3 lag)	0	pos (2,8 lags)
	TP	neg (1-8 lags)	0	0

Figure 13: Summary of empirical tests for Granger-causality in the market microstructure.

In summary, the tendency I observed was that increases in market returns were caused by fund flow increases, average forecast decreases, and lower dispersion of analyst forecast, albeit, the last one is a very weak relationship. From this I conclude that there are some signs of temporary inefficiencies, but the efficient market hypothesis cannot be falsified, even in these emerging markets.

Further research areas which were beyond the scope of my dissertation include the impact of market liquidity and also examining the impact of analysts based on their past performance and their experience. Also, optimising trading algorithms and

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strategies with accounting for transaction costs, and investigating whether contrarian trading strategies yield better results can be topics to further explore.

I presented my results in this dissertation and showed the value of analyst forecast and fund flow data in understanding returns through the example of Emerging European equity markets. With wider-spread availability of the analyst forecast and fund flow data, I hope more academic research would cover the microstructure of the cash equity business, that would ultimately benefit investors and capital markets.

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8. Glossary

Consensus	It is the average forecast of equity analysts covering a stock. Consensus may refer to target prices and earnings estimates.
Coverage	The act of providing analysis for a stock by issuing research reports including target prices and recommendations on a regular basis.
Developed markets	Includes stock markets of USA, Canada, Western Europe, Asia, Japan
Downgrade (of a recommendation)	When a new recommendation is on a lower grade than the previous one. Going from strong buy to buy, buy to neutral and so on.
Downside	The negative difference (in %) between the target price and the current closing price of the stock.
Earnings estimate	Estimation of earnings per share (EPS) for a stock by an analyst for a given date. May also be referred to as earnings forecast.
EMEA	Europe, Middle East, Africa
Emerging markets	Includes EMEA, LatAm (Latin America)
Equity Analyst	Is the person authorised to cover stocks on behalf of a brokerage firm. Their qualification is usually supported by professional exams (e.g. CFA) and regulatory approvals (e.g. FSA exam).
Fair value	Theoretical economic value based on present value of future cash flows.
Forecast	In my dissertation, I will collectively refer to target prices and the recommendations as analyst forecasts or simply forecasts.
Maintenance or reiteration (of a recommendation)	When a new recommendation is not changed from the previous one.

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Market value	Valuation based on stock price, as priced in by the market.
Opinion	Used interchangeably with Analyst forecast. *See* Forecast.
Pricing date	The date on which pricing is carried out for a research note. It is usually 1-2 days prior to the publication date, allowing time for final editing and production.
Publication date	The date on which research notes are published, i.e. dispersed to clients and data source providers.
Recommendation	Qualitative rating of a stock given on an ordinal scale referring to the analysts' advice to purchase, to hold on to or to dispose of the stock.
Research note or equity research	The written product of an equity analyst or a team of analysts that includes the target price and recommendation on the covered stock, and quantitative and qualitative assessment of the investment case.
Stock universe	The whole set of stocks covered by a brokerage firm.
Target price	The fair value of the stock 12 months from now.
Upside	The positive difference (in %) between the target price and the current closing price of the stock.
Earnings forecast	See earnings estimate
Upgrade (of a recommendation)	When a new recommendation is on a higher grade than the previous one. Going from strong sell to sell, sell to neutral and so on.

9. References

1. Alexakis, C. – Niarchos, N. – Patra, T. – Poshakwale, S. (2004): The Dynamics between Stock Returns and Mutual Fund Flows: Empirical Evidence from the Greek Market. International Review of Financial Analysis 14, pp. 559-569. DOI reference: http://dx.doi.org/10.1016/j.irfa.2004.10.019

2. Arrow, K. (1981): Risk Perception in Psychology and Economics. Institute for Mathematical Studies in the Social Sciences, Stanford University, Stanford, Calif. DOI reference: http://dx.doi.org/10.1111/j.1465-7295.1982.tb01138.x

3. Ball, R. – Kothari, S. (1989): Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlation in Returns. Journal of Financial Economics, 25 (1), pp. 51-74. DOI reference: http://dx.doi.org/10.1016/0304-405x(89)90096-2

4. Barber, B. – Odean, T. (2000): Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. The Journal of Finance, 55 (2), pp. 773-806. DOI reference: http://dx.doi.org/10.2139/ssrn.219228

5. Barry, C. – Brown, S. (1985): Differential Information and Security Market Equilibrium. The Journal of Financial and Quantitative Analysis, 20 (4), pp. 407-422. DOI reference: http://dx.doi.org/10.2307/2330758

6. Barberis, N. – Shleifer, A. – Vishny, R. (1998): A Model of Investor Sentiment. Journal of Financial Economics, 49 (3), pp. 307-343. DOI reference: http://dx.doi.org/10.3386/w5926

7. Barberis, N. – Thaler, R. (2002): A Survey of Behavioral Finance. NBER Working Papers 9222, National Bureau of Economic Research, Inc. DOI reference: http://dx.doi.org/10.3386/w9222

8. Basu, S. (1977): Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. The Journal of Finance, 32 (3), pp. 663-682. DOI reference: http://dx.doi.org/10.2307/2326304

9. Basu, S. (1983): The Relationship between Earnings' Yield, Market Value and Return for NYSE Common Stocks: Further Evidence. Journal of Financial Economics, 12 (1), pp. 129-156. DOI reference: http://dx.doi.org/10.1016/0304-405x(83)90031-4

10. Bauer, G. (2012): A Taxonomy of Market Efficiency, Bank of Canada working paper, pp. 37-40. http://www.bankofcanada.ca/wp-content/uploads/2012/01/fsr-1204-bauer.pdf download date: 10th May, 2012.

11. Bélyácz, I. (2010): Kockázat vagy bizonytalanság? Elmélettörténeti töredék a régi dilemmáról, Közgazdasági Szemle, LVII., pp. 652–665.

12. Bengtsson, E. (2009): European Investment Fund Flows and Financial Stability, Journal of Asset Management, 10, pp. 293 – 304. DOI reference: http://dx.doi.org/10.1057/jam.2009.30

13. Black, F. – Jensen, M. – Scholes, M. (1972): The Capital Asset Pricing Model: Some Empirical Tests, Studies in the Theory of Capital Markets, 81, pp. 79-121.

14. Black, F. – Scholes, M. (1973): The Pricing of Options and Corporate Liabilities, The Journal of Political Economy, 81 (3), pp. 637-654. DOI reference: http://dx.doi.org/10.1086/260062

15. Bodie, Z. – Kane, A. – Marcus, A. (2003): Investments, McGraw-Hill, Irwin, 5th edition.

16. Boyer, B. – Zheng, L. (2002): Who Moves the Market? A Study of Stock Prices and Investment Cashflows, http://papers.ssrn.com/sol3/papers.cfm?_abstract_id=342681 download date: 2nd May, 2012. DOI reference: http://dx.doi.org/10.2139/ssrn.342681

17. Bradshaw, M. – Brown, L. – Atlanta, G. (2006): Do Sell-Side Analysts Exhibit Differential Target Price Forecasting Ability? http://www.alumni.agsm.edu.au/agsm/web.nsf/Attachments ByTitle/Paper_Mark+Bradshaw_20060612_fix.pdf/$FILE/Paper_Mark+Bradshaw_2

0060612_fix.pdf download date: 31st March, 2012. DOI reference: http://dx.doi.org/10.2139/ssrn.698581

18. Brav, A. – Lehavy, R. (2003): An Empirical Analysis of Analysts' Target Prices: Short-Term Informativeness and Long-Term Dynamics, Journal of Finance, 58 (5), pp. 1933-1967. DOI reference: http://dx.doi.org/10.2139/ssrn.266180
19. Carhart, M. (1997): On Persistence in Mutual Fund Performance, The Journal of Finance, 52 (1), pp. 57-82. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1997.tb03808.x
20. Cha, H. – Kim, J. (2007): Stock Prices and Equity Mutual Fund Flows: A Macro Approach, Working Paper, Oklahoma State University.
21. Chatfield – Roberst, J. (2006): Fundology, The Secrets of Successful Fund Investing, Harriman House Publishing.
22. Chen, J. – Hong, H. – Stein, J. (2001): Breadth of Ownership and Stock Returns. NBER Working Papers 8151, National Bureau of Economic Research, Inc. DOI reference: http://dx.doi.org/10.3386/w8151
23. Chopra, N. – Lakonishok, J. – Ritter, J. (1992): Measuring Abnormal Performance: Do Stocks Overreact? Journal of Financial Economics, 31 (2), pp. 235-268. DOI reference: http://dx.doi.org/10.1016/0304-405x(92)90005-i
24. Clare, A. – Thomas, S. (1995): The Overreaction Hypothesis and the UK Stock Market, Journal of Business Finance and Accounting, 22 (7), pp. 961-961. DOI reference: http://dx.doi.org/10.1111/j.1468-5957.1995.tb00888.x
25. Cowles, A. – Jones, H. (1937): Some A Posteriori Probabilities in Stock Market Action. Econometrica, 5 (3), pp. 280-294. DOI reference: http://dx.doi.org/10.2307/1905515
26. Cox, D.R. (1972): The Analysis of Multivariate Binary Data, Applied Statistics, 21 (2) pp. 113-120. DOI reference: http://dx.doi.org/10.2307/2346482

27. Cutler, D. – Poterba, J. – Summers, L. (1989): What Moves Stock Prices? NBER Working Papers 2538, National Bureau of Economic Research, Inc. DOI reference: http://dx.doi.org/10.3386/w2538

28. Cyert, R. – DeGroot, M. (1974): Rational Expectations and Bayesian Analysis, The Journal of Political Economy, 82 (3), pp. 521-536. DOI reference: http://dx.doi.org/10.1086/260210

29. Damodaran, A. – Liu, Ch. (1993): Insider Trading as a Signal of Private Information, The Review of Financial Studies, 6 (1), pp. 79-119. http://dx.doi.org/10.1093/rfs/2.4.607

30. Damodaran, A. (1989): The Weekend Effect in Information Releases: a Study of Earnings and Dividend Announcements, The Review of Financial Studies, 2 (4), pp. 607-623. http://dx.doi.org/10.1093/rfs/2.4.607

31. Daniel, K. – Hirshleifer, D. – Subrahmanyam, A. (1998): Investor Psychology and Security Market Under-and Overreactions, The Journal of Finance, 53 (6), pp. 1839-1885. DOI reference: http://dx.doi.org/10.1111/0022-1082.00077

32. Davidson, W. N. – Dutia, D. (1989): A Note on the Behaviour of Security Returns: A Test of Stock Market Overreaction and Efficiency, Journal of Financial Research 13 (3), pp. 245-253.

33. Davis, M. – Etheridge, A. (2006): Louis Bachelier's Theory of Speculation: The Origins of Modern Finance, Princeton University Press.

34. De Bondt, W. – Thaler, R. (1985): Does the Stock Market Overreact? The Journal of Finance, 40 (3), pp. 793-805. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1985.tb05004.x

35. DeCanio, S. (1979): Rational Expectations and Learning from Experience, The Quarterly Journal of Economics, 93 (1), pp. 47-57. DOI reference: http://dx.doi.org/10.2307/1882597

36. Denis, G. – Dimitri, V. (2002): Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs, Journal of Financial Economics, 66 (2-3), pp. 361-407. DOI reference: http://dx.doi.org/10.1016/s0304-405x(02)00228-3

37. Diamond, D. – Verrecchia, R. (1987): Constraints on Short-Selling and Asset Price Adjustment to Private Information, Journal of Financial Economics, 18 (2), pp. 277-311. DOI reference: http://dx.doi.org/10.1016/0304-405x(87)90042-0

38. Diether, K. – Malloy, C. – Scherbina, A. (2002): Differences of Opinion and the Cross Section of Stock Returns, The Journal of Finance, 57 (5), pp. 2113-2141. DOI reference: http://dx.doi.org/10.1111/0022-1082.00490

39. Dubovsky, D.A. (2010): Mutual Fund Portfolio Trading and Investor Flow, Journal of Banking & Finance, 34, pp. 802-812. DOI reference: http://dx.doi.org/10.2139/ssrn.1140348

40. Edelen, R. (1999): Investor Flows and the Assessed Performance of Open–End Mutual Funds, Journal of Financial Economics 53, pp. 439–466. DOI reference: http://dx.doi.org/10.1016/s0304-405x(99)00028-8

41. Fama, E. (1970): Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance, 25 (2), pp. 383-417. DOI reference: http://dx.doi.org/10.2307/2325486

42. Fama, E. (1991): Efficient Capital Markets: II, The Journal of Finance, 46 (5), pp. 1575-1617. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1991.tb04636.x

43. Fama, E. (1998): Market Efficiency, Long-Term Returns, and Behavioral Finance, Journal of Financial Economics, 49 (3), pp. 283-306. DOI reference: http://dx.doi.org/10.2139/ssrn.15108

44. Fama, E. – Fisher, L. – Jensen, M. – Roll, R. (1969): The Adjustment of Stock Prices to New Information, International Economic Review, 10 (1), pp. 1-21. DOI reference: http://dx.doi.org/10.2307/2525569

45. Fama, E. – French, K. (1993): Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics, 33 (1), pp. 3-56. DOI reference: http://dx.doi.org/10.1016/0304-405x(93)90023-5

46. Fama, E.–French, K. (1996): Multifactor Explanations of Asset Pricing Anomalies, The Journal of Finance, 1 (1), pp. 55–84. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1996.tb05202.x

47. Fama, E. – French, K. (2011): Size, Value, and Momentum in International Stock Returns, Tuck School of Business Working Paper No. 2011-85. DOI reference: http://dx.doi.org/10.2139/ssrn.1720139

48. Fortune, P. (1998): Mutual Funds, Part II: Fund Flows and Security Returns, New England Economic Review, January/February, 3–22.

49. Francisco, C. (1987): The Capital Asset Pricing Model with Non-Homogeneous Expectations: Theory and Evidence on Systematic Risks to the Beta, Harvard University and Philippine Institute for Development Studies, pp. 1-57.

50. French, K. R. – Roll, R. (1986): Stock Return Variances: The Arrival of Information and the Reaction of Traders, Journal of Financial Economics, 17 (1), pp. 5-26. DOI reference: http://dx.doi.org/10.1016/0304-405x(86)90004-8

51. Fridson, M.S. (2000): Semi-Annual Seasonality in High-Yield Bond Returns, Journal of Portfolio Management 26, pp. 102–111. DOI reference: http://dx.doi.org/10.3905/jpm.2000.319768

52. Froot, K. A. – O'Connell, P. G. J. – Seasholes, M. S. (2001): The Portfolio Flows of International Investors, Journal of Financial Economics 59 (2), pp. 151-193. DOI reference: http://dx.doi.org/10.1016/s0304-405x(00)00084-2

53. Gleason, C. – Johnson, W. – Li, H. (2007): The Earnings Forecast Accuracy, Valuation Model Use, and Price Target Performance of Sell-Side Equity Analysts, Tech. rep., Working paper, University of Iowa, http://www.mccombs.utexas.edu/news/research_calendar/

ACCT_Gleason_9_22_06.pdf download date: 30th March, 2012. DOI reference: http://dx.doi.org/10.2139/ssrn.930720

54. Goetzmann, W. – Massa, M. (1999): Index Funds and Stock Market Growth, National Bureau of Economic Research, Inc. NBER Working Papers 7033. DOI reference: http://dx.doi.org/10.3386/w7033
55. Grossman, S. – Stiglitz, J. (1980): On the Impossibility of Informationally Efficient Markets, The American Economic Review, 70 (3), pp. 393-408. DOI reference:
56. Grossman, S. – Stiglitz, J. (1982): On the Impossibility of Informationally Efficient Markets: Reply, The American Economic Review, 72 (4), p. 875. DOI reference:
57. Haltiwanger, J. – Waldman, M. (1985): Rational Expectations and the Limits of Rationality: an Analysis of Heterogeneity, The American Economic Review, 75 (3), pp. 326-340. DOI reference:
58. Harrison, J. – Kreps, D. (1978): Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations, The Quarterly Journal of Economics, 92 (2), pp. 323-336. DOI reference: http://dx.doi.org/10.2307/1884166
59. Hirshleifer, D. (2001): Investor Psychology and Asset Pricing, The Journal of Finance, 56 (4), pp. 1533-1597. DOI reference: http://dx.doi.org/10.1111/0022-1082.00379
60. Hendry, S. – King, M. (2004): The Efficiency of Canadian Capital Markets: Some Bank of Canada Research, Bank of Canada Review, pp. 5–17.
61. Hommes, C. (2005): Heterogeneous Agent Models in Economics and Finance, Tinbergen Institute Discussion Paper, TI 2005-056/1. DOI reference: http://dx.doi.org/10.2139/ssrn.742384
62. Hommes, C. (2010): The Heterogeneous Expectations Hypothesis: Some Evidence from the Lab, International Research Forum on Monetary Policy, http://www.federalreserve.gov/events/conferences/irfmp2010/HTML/paper6/index.html download date: 5th June, 2012. DOI reference: http://dx.doi.org/10.1016/j.jedc.2010.10.003

63. Hong, H. – Kubik, J. – Solomon, A. (2000): Security Analysts' Career Concerns and Herding of Earnings Forecasts, The RAND Journal of Economics, Vol. 31, No. 1, pp. 121-144. DOI reference: http://dx.doi.org/10.2307/2601032

64. Hong, H. – Stein, J. (1999): Differences of Opinion, Rational Arbitrage and Market Crashes, NBER Working Papers 7376. DOI reference: http://dx.doi.org/10.3386/w7376

65. Hosmer, D.W. – Lemeshow, S. (2000): Applied Logistic Regression, 2nd edition, Wiley. DOI reference: http://dx.doi.org/10.1002/0471722146

66. Huberman, G. – Regev, T. (2001): Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar, The Journal of Finance, 56 (1), pp. 387-396. DOI reference: http://dx.doi.org/10.1111/0022-1082.00330

67. Ippolito, R. (1992): Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, Journal of Law and Economics 35, pp. 45-69. DOI reference: http://dx.doi.org/10.1086/467244

68. Jegadeesh, N. – Titman, S. (1993): Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, The Journal of Finance, 48 (1), pp. 65-91. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1993.tb04702.x

69. Jensen, M. (1968): The Performance of Mutual Funds in the Period 1945-1964, Journal of Finance, 23 (2), pp. 389-416. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1968.tb00815.x

70. Jensen, M. (1978): Some Anomalous Evidence Regarding Market Efficiency, Journal of Financial Economics 6 (2/3), pp. 95-101. DOI reference: http://dx.doi.org/10.2139/ssrn.244159

71. Johnson, T. (2004): Forecast Dispersion and the Cross Section of Expected Returns, The Journal of Finance, 59 (5), pp. 1957-1978. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.2004.00688.x

72. Jotikasthira, C. – Lundblad, C. – Ramadorai, T. (2012): Asset Fire Sales and Purchases and the International Transmission of Financial Shocks, CEPR Discussion

Papers. www.epfr.com download date: 30th January, 2011. DOI reference: http://dx.doi.org/10.2139/ssrn.1523628

73. Kahneman, D. – Slovic, P. – Tversky, A. (1982): Judgment Under Uncertainty: Heuristics and Biases, Cambridge University Press. DOI reference: http://dx.doi.org/10.1017/cbo9780511809477

74. Kahneman, D. – Tversky, A. (1973): On the Psychology of Prediction, Psychological Review, 80 (4), pp. 237-251. DOI reference: http://dx.doi.org/10.1037/h0034747

75. Kahneman, D. – Tversky, A. (1979): Prospect Theory: An Analysis of Decision Under Risk, Econometrica, 47 (2), pp. 263-291. DOI reference: http://dx.doi.org/10.2307/1914185

76. Kaminsky, G. L. – Lyons, R. K. – Schmukler, S. L. (2001): Mutual Fund Investment in Emerging Markets: An Overview, The World Bank Economic Review 15 (2), pp. 315-340. DOI reference: http://dx.doi.org/10.1007/978-1-4757-3314-3_7

77. Kanne, S. – Kreutzmann, D. (2008): Recommendations and the Performance of Target Price Changes, http://cfr-cologne.de/download/kolloquium/2009/kanne-kreutzmann.pdf download date: 30th April, 2012. DOI reference:

78. Klobucnik, J. – Kreutzmann, D. – Sievers, S. – Kanne, S. (2012): To Buy or Not to Buy? The Value of Contradictory Analyst Signals, http://dx.doi.org/10.2139/ssrn.2012599 download date: 6th May, 2012. DOI reference: http://dx.doi.org/10.1007/s11408-012-0196-z

79. Kovács, E. (2006): Pénzügyi adatok statisztikai elemzése, egyetemi tankönyv, Budapesti Corvinus Egyetem.

80. Lamont, O. (2004): Go Down Fighting: Short Sellers vs. Firms, NBER Working Papers 10659. DOI reference: http://dx.doi.org/10.3386/w10659

81. Lee, C. – Swaminathan, B. (2000): Price Momentum and Trading Volume, The Journal of Finance, 55 (5), pp. 2017-2069. DOI reference: http://dx.doi.org/10.2139/ssrn.92589

82. Lintner, J. (1965): The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, Review of Economics and Statistics, 47, pp. 13-37. DOI reference: http://dx.doi.org/10.2307/1924119

83. Lo, A. W. – Mackinlay, A. C. (1999): A Non-Random Walk down Wall Street, Princeton University Press. DOI reference: http://dx.doi.org/10.1007/s00712-003-0592-y

84. Loh, R. – Mian, G. (2006): Do accurate earnings forecasts facilitate superior investment recommendations? Journal of Financial Economics, 80 (2), pp. 455-483. DOI reference: http://dx.doi.org/10.1016/j.jfineco.2005.03.009

85. Malkiel, B. (1982): Risk and Return: A New Look. NBER Working Papers 0700. DOI reference: http://dx.doi.org/10.3386/w0700

86. Malkiel, B. (1973): A Random Walk Down Wall Street. New York, W. W. Norton and Company, Inc. DOI reference: http://dx.doi.org/10.5860/choice.41-0431

87. Malkiel, B. (2003): The Efficient Market Hypothesis and its Critics, The Journal of Economic Perspectives, 17 (1), pp. 59-82. DOI reference: http://dx.doi.org/10.1257/089533003321164958

88. Mankiw, N. – Zeldes, S. (1991): The Consumption of Stockholders and Nonstockholders, Journal of Financial Economics, 29 (1), pp. 97-111. DOI reference: http://dx.doi.org/10.1016/0304-405x(91)90015-c

89. Marquering, W. – Nisser, J. – Valla, T. (2006): Disappearing Anomalies: A Dynamic Analysis of the Persistence of Anomalies, Applied Financial Economics, 16 (4), pp. 291-302. DOI reference: http://dx.doi.org/10.1080/09603100500400361

90. McClure, B. (2010): Earnings Forecasts: A Primer, http://www.investopedia.com/articles/ stocks/06/earningsforecasts.asp download date: 31st March, 2012.

91. McNichols, M. – O'Brien, P. (1997): Self-Selection and Analyst Coverage, Journal of Accounting Research, 35, pp. 167-199. DOI reference: http://dx.doi.org/10.2307/2491460

92. Mehra, R. (2003): The Equity Premium: Why Is It a Puzzle? NBER Working Papers 9512. DOI reference: http://dx.doi.org/10.3386/w9512

93. Mehra, R. – Prescott, E. (1985): The Equity Premium: A Puzzle, Journal of Monetary Economics, 15 (2), pp. 145-161. DOI reference: http://dx.doi.org/10.3386/w9512

94. Meyer, B. – Anamootoo, J. – Schmitz, I. (2006): The Predictive Power of Weekly Fund Flows. Equity Strategy, Deutsche Bank, http://www.epfr.com/case_studies/DB_PredictivePower.pdf download date: 15th June, 2011. DOI reference:

95. Meyer, B. (2010): The Value of Weekly Fund Flow Data – How Fund Flow Data Helps to Improve Tactical Asset Allocation. Cross Asset Strategy, Commerzbank, http://www.epfr.com/Case_Studies/CAF_Commerzbank.pdf download date: 1st February, 2012. DOI reference:

96. Miao, Y. – Pant, M. (2012): Coincident Indicators of Capital Flows, IMF Working Paper, WP/12/55, http://www.imf.org/external/pubs/ft/wp/2012/wp1255.pdf download date: 30th March, 2012. DOI reference:

97. Mikhail, M. – Walther, B. – Willis, R. (2004): Do Security Analysts Exhibit Persistent Differences in Stock Picking Ability? Journal of Financial Economics, 74 (1), pp. 67-91. DOI reference: http://dx.doi.org/10.2139/ssrn.299667

98. Miller, E. (1977): Risk, Uncertainty, and Divergence of Opinion, The Journal of Finance, 32 (4), pp. 1151-1168. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1977.tb03317.x

99. Miller, M. (1986): Behavioral Rationality in Finance: The Case of Dividends, Journal of Business, 59 (4), pp. 451-468. DOI reference: http://dx.doi.org/10.1086/296380

100. Modigliani, F. – Miller, M. (1958): The Cost of Capital, Corporation Finance and the Theory of Investment, The American Economic Review, 48 (3), pp. 261-297. DOI reference:

101. Nagel, S. (2005): Short Sales, Institutional Investors and the Cross-Section of Stock Returns, Journal of Financial Economics, 78 (2), pp. 277-309. DOI reference: http://dx.doi.org/10.1016/j.jfineco.2004.08.008

102. Neumann, J. – Morgenstern, O. – Kuhn, H. – Rubinstein, A. (2007): Theory of Games and Economic Behavior, 60th Anniversary Edition, Princeton University Press, New Jersey. DOI reference: http://sf.oxfordjournals.org/content/24/2/245

103. Nocera, J. (2009): Poking Holes in a Theory on Markets. The New York Times. http://www.nytimes.com/2009/06/06/business/06nocera.html?_r=1&scp=1&sq=efficient%20market&st=cse download date: 30th November, 2011. DOI reference:

104. Odean, T. (1998): Volume, Volatility, Price, and Profit When All Traders Are Above Average, The Journal of Finance, 53 (6), pp. 1887-1934. DOI reference: http://dx.doi.org/10.2139/ssrn.94141

105. Odean, T. (1999): Do Investors Trade Too Much? The American Economic Review, 89 (5), pp. 1279-1298. DOI reference: http://dx.doi.org/10.1257/aer.89.5.1279

106. Qu, S. – Starks, L. – Yan, H. (2004): Risk, Dispersion of Analyst Forecasts and Stock Returns, University of Texas at Austin, http://www2.agsm.edu.au/agsm/web.nsf/Attachments ByTitle/Paper_Hong+Yan_2003/$FILE/Paper_Hong+Yan_2003.pdf download date: 25th February, 2012.

107. Radnai, M. (2002): Árazási hiba a határidős indexpiacokon, Közgazdasági Szemle, XLIX., pp. 905-927.

108. Remolona, E. M. – Kleinman, P. – Gruenstein, D. (1997): Market Returns and Mutual Fund Flows, Economic Policy Review 3, pp. 33-52.

109. Roll, R. (1977): A Critique of Asset Pricing Theory's Tests Part I: On Past and Potential Testability of the Theory, Journal of Financial Economics, 4, pp. 129-176. DOI reference: http://dx.doi.org/10.1016/0304-405x(77)90009-5

110. Roll, R. (1984): Orange Juice and Weather, The American Economic Review, 74 (5), pp. 861-880.

111. Sharpe, W. (1964): Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk, The Journal of Finance, 19 (3), pp. 425-442. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1964.tb02865.x

112. Shiller, R. (1981): Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? The American Economic Review, 71 (3), pp. 421-436. DOI reference: http://dx.doi.org/10.3386/w0456

113. Shleifer, A. – Vishny, R. (1997): The Limits of Arbitrage, The Journal of Finance, 52 (1), pp. 35-55. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1997.tb03807.x

114. Stevens, S. S. (1946): On the Theory of Scales of Measurement, Science, Vol. 103, No. 2684, pp. 677–680. DOI reference: http://dx.doi.org/10.1126/science.103.2684.677

115. Stevens, S.S. (1951): Mathematics, Measurement and Psychophysics, In Stevens (Ed.) Handbook of Experimental Psychology, pp. 1–49. New York: Wiley.

116. Stickel, S. (1992): Reputation and Performance Among Security Analysts, The Journal of Finance, Vol. 47, Issue 5, pp. 1811-1836. DOI reference: http://10.1111/j.1540-6261.1992.tb04684.x

117. Stout, L. (2004): The Mechanisms of Market Inefficiency: An Introduction to the New Finance. UCLA School of Law, http://www.escholarship.org/uc/item/5tc4j0qn download date: 28th January, 2012. DOI reference: http://dx.doi.org/10.2139/ssrn.470161

118. Thaler, R. (1999): The End of Behavioral Finance, Financial Analysts Journal, 55 (6), pp. 12-17. DOI reference: http://dx.doi.org/10.2469/faj.v55.n6.2310

119. Thaler, R. (2009): Markets Can Be Wrong and the Price is Not Always Right, The Financial Times, http://www.ft.com/cms/s/0/efc0e92e-8121-11de92e700144feabdc0.html?n click_check=1 download date: 1st March, 2012.

120. The Economist (2009): Efficiency and Beyond, The Economist. 16th July, 2011.

121. Varian, H. (1989): Financial Risk: Theory, Evidence and Implications: Proceedings of the 11th Annual Economic Policy Conference of the Federal Reserve Bank of St. Louis. Kluwer Academic Publishers.

122. Walter, Gy. – Berlinger, E. (1999): Faktormodellek az értékpapírpiacon, Bankszemle, 43 (4), pp. 34-43.

123. Warther, V.A. (1995): Aggregate Mutual Fund Flows and Security Returns, Journal of Financial Economics 39, pp. 209–235. DOI reference: http://dx.doi.org/10.1016/0304-405x(95)00827-2

124. Womack, K. (1996): Do Brokerage Analysts' Recommendations Have Investment Value? Journal of Finance, 51 (1), pp. 137-167. DOI reference: http://dx.doi.org/10.1111/j.1540-6261.1996.tb05205.x

125. Working, H. (1934): A Random Difference Series for Use in the Analysis of Time Series, Journal of the American Statistical Association, 29 (185), pp. 11-24. DOI reference: http://dx.doi.org/10.2307/2278456

126. Zarowin, P. (1990): Size, Seasonality, and Stock Market Overreaction, Journal of Financial and Quantitative Analysis, 25 (1), pp. 113-125. DOI reference: http://dx.doi.org/10.2307/2330891

DOI: 10.14267/phd.2015019

Own publications:

1. Naffa, H. – Kaliczka, N. (2011): Az állami szerepvállalás egy modellje a lejárt követelések piacán, Hitelintézeti szemle 10:(2) *pp. 93-107.*
2. Kovács, E. – Dömötör, B. – Naffa, H (2011): Investment Decision in Crises: A Study of Private Pension Fund Investments, Acta Oeconomica 61:(4) pp. 389-412. DOI reference: http://dx.doi.org/10.1556/AOecon.61.2011.4.1
3. Kaliczka, N – Naffa, H. (2010): Természetes jelzések a megbízó-ügynök koalíció jövedelmének hitelesítésében, Vezetéstudomány 41:(4) pp. 45-54.
4. Naffa, H. (2009): Eszközárazási anomáliák többváltozós modellje, Hitelintézeti szemle 8:(6) pp. 516-527.
5. Naffa, H. (2009): A Multifactor Approach in Understanding Asset Pricing Anomalies, Budapesti Értéktőzsde, Budapest, Kochmeister díj.