Erasmus University Rotterdam
Erasmus School of Economics

INVESTOR REACTIONS TO EARNINGS SURPRISES: A LEARNING PERSPECTIVE

A Master's Thesis
in
Financial Economics
by

Agnieszka Anna Pawlak

Student ID: 435581

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science in Economics and Business

Thesis Supervisor: **Dr. Sjoerd van den Hauwe**
Second Assessor: **Dr. Jan Lemmen**

November 2017

The thesis of Agnieszka Anna Pawlak was reviewed and approved* by the following:

Dr. Sjoerd van den Hauwe
Assistant Professor of Finance
Thesis Advisor, Chair of Committee

Dr. Jan Lemmen
Lecturer of Finance
Thesis Committee Member

*Signatures are on file in the Graduate School.

Abstract

This thesis investigates investor reactions to earnings announcements from a learning perspective. I find that negative earnings surprises exert larger impact on stock returns of younger firms than those that are positive. This asymmetry decreases over the course of firm's aging. I also find that among investors, institutional traders are more responsive to earnings surprises in the direction of the surprise sign. The decreasing differential in the institutional investors' reaction to the opposite surprise signs over the course of company's aging indicates that this investor class resolves their uncertainty about stocks' actual profitability during earnings announcements. Overall, contrary to Lakonishok et al. (1994), I find no evidence that investors overreacting to good/bad news are naïve, and thereby that the return differential between growth (glamour) and value stocks arises due to their naivety. Instead, results of my analyses suggest that such investors are sophisticated and well informed. Building on Pástor and Veronesi (2003), I find that the asymmetry in the magnitudes of overreaction to unexpected earnings surprises for different stock categories and the return differential between growth and value stocks appear to stem from resolving uncertainty about stocks' true profitability during quarterly earnings announcements.

Keywords : earnings surprises, glamour, growth, individual investors, institutional investors, learning, old stocks, return differential, uncertainty, value, young stocks

Table of Contents

List of Figures

List of Tables

List of Symbols

θ In case of Bayesian Learning, the true signal, p. 12

$\tilde{\theta}$ In case of Bayesian Learning, the observed signal, p. 13

σ In case of Bayesian Learning, the standard deviation of each observation (the magnitude of noise), p. 13

$\tilde{\sigma}$ In case of Bayesian Learning, observed standard deviation of posterior beliefs about the signal, p. 13

$\rho_{x,y}$ Covariance coefficient between random variables X and Y, p. 35

Acknowledgments

First and foremost, I would like to express my gratitude to my advisor Prof. Sjoerd van den Hauwe for his time, assistance and patience throughout the process of writing my Master's Thesis at Erasmus University Rotterdam (EUR). He has been a valuable guide in my rigorous journey in this graduate school.

Special thanks goes to Prof. Sjoerd van Bekkum for inspiring me with the research topic and for helping me form my initial thoughts on this work. I would also like to thank Prof. Terrance Odean from the University of California, Berkeley for sharing his dataset on individual trades at a large discount brokerage firm, which has been essential to test several of my hypotheses in this thesis.

I am very grateful to my good friends in Poland and in Italy for fueling me with positive energy. Furthermore, I want to thank my colleagues around EUR for making my life at this graduate school not only academically but also a socially fruitful time.

Finally, I would particularly like to thank my beloved family for their love, dedication, and support that they have given to me throughout all my life. Without them nothing would be possible.

Dedication

To my family...

Chapter 1

Introduction

This thesis explores investor reactions to earnings announcements from a learning perspective. In particular, it tries to answer the question whether the higher impact of negative earnings surprises on stock returns of growth (glamour) firms arises due to a higher level of uncertainty about these stocks' profitability. My hypotheses for testing this assumption are developed based on a detailed examination of current financial literature on the areas of earnings surprises, learning about stock profitability and investor behavior.

One of the paradoxes observed in the financial market is about stock returns of growth companies: although growth firms are believed to have rosy prospects, their returns are on average inferior relative to the returns of value stocks, whose outlooks are not that propitious. Throughout the recent decades many financial scholars have undertaken investigations in order to explain such anomaly. Most of them have agreed that the return differential is caused by the erroneous expectations about the future stock performance. Investors tend to be overly optimistic about the future profitability of growth stocks and overly pessimistic about the future prospects of value stocks. When their expectations are not met, a respective decrease in the returns of growth companies and an increase in the returns of value companies is observed. In other words, an earnings surprise occurring in the direction that is inverse to the direction of expectations exerts a greater influence on stock returns than a surprise occurring in the direction congruous with the expectations. The reason for this is that in the former case investors experience the dual astonishment – related to the surprise itself as well as its adversarial feature. Some authors argue that this phenomenon stems from the investors' naïve extrapolation of stocks' past performance into the future (Lakonishok et. al, 1994), and others claim that the source of this expectation error is the investors' indiscriminate reliance on the analysts' forecasts regarding company's future earnings (La Porta, 1996; Dechow and Sloan, 1997).

A revision of erroneous expectations takes place at the time of quarterly earnings announcements. Skinner and Sloan (2002) demonstrate that not only negative surprises are followed by negative stock returns and positive earnings surprises trigger positive stock returns, but, strikingly, the impact of negative news on the subsequent realized return is significantly larger than the impact of positive news. This asymmetry in the responses to earnings surprises increases as company's growth rate increases – returns of the growth companies are significantly more responsive to the earnings surprises than returns of the value companies. The results of Skinner and Sloan (2002) provide strong support for the notion that the return differential between glamour and value stocks arises due to revisions of the erroneous expectations about stocks' profitability that occur during the earnings announcements. However, these results also raise the question of what creates the asymmetry in the responsiveness to the unexpected for a given stock class surprises. Specifically, why the magnitude of punishment for growth stocks related to negative news is significantly higher than the magnitude of reward for value stocks reporting positive news. So far, this issue has not been addressed in the financial research literature.

In this research I try to find the source of this phenomenon by examining the theory of learning in financial markets. My main prediction is that the higher impact of negative earnings surprises on the abnormal stock returns of growth firms stems from the fact that investors learn about the true profitability of these companies. Growth stocks tend to be in general stocks of young companies, whereas value stocks are mainly stocks of older firms. As investors deal with a higher level of uncertainty when trading growth stocks, any resolution of such uncertainty triggers analogously a stronger impact on their stock returns. Thus, I assume that negative surprises have greater impact on the returns of young (growth) stocks than positive surprises on the returns of old (value) stocks, because of two factors: the dual astonishment (a surprise itself and its inverse-to-expected direction) and the higher level of uncertainty. This intuition is based on the findings of Pástor and Veronesi

(2003). Specifically, the valuation of a company increases with the uncertainty about firm's average profitability. An older firm tends to have a lower *market-to-book* ratio (a proxy for the expected growth prospects) than an otherwise similar younger firm, because over the course of company's aging investors learn about the true profitability of such a firm and the uncertainty gets resolved.

The conviction that the uncertainty about stocks' average profitability is the main driver of the asymmetrical responsiveness to earnings surprises seems to explain also other phenomena related to growth and value stocks, as well as to the firm size:

- ▷ lower level of accuracy in the analysts' forecasts regarding growth stocks compared to the accuracy of forecasts of value stocks (see La Porta, 1996);
- ▷ lower level of accuracy in the analysts' forecasts regarding smaller stocks (see Brown et al., 1987);
- ▷ higher return differential between these two classes of stocks in the subsample of the smallest firms (see La Porta et al., 1997).

The forecast accuracy seems to be strongly correlated with the level of certainty about stocks' true profitability. While assessing prospects of growth firms, analysts deal with huge uncertainty as such companies do not possess a long track of past performance. Also smaller stocks are subjected to more vagueness about their future profitability since they are characterized by lower transparency than otherwise similar larger stocks. Thus, I expect the asymmetry in the responsiveness to earnings surprises to be negatively correlated with the firm size.

In order to verify my assumptions, I develop three hypotheses that I test via linear regressions. First of all, I examine whether investors do resolve their uncertainty about stock profitability at the time of earnings announcements. Thereafter, I investigate whether the increased overreaction to the negative surprises stems from the higher level of such uncertainty. My sample combines the data on quarterly earnings announcements and the related stock returns of the universe of companies publicly traded on the stock market in the United States of America in the years 1991–2010.

The results of my work show that the impact of earnings surprises on the stock returns decreases over the course of firm's aging. Thus, investors appear to indeed resolve uncertainty about stock profitability during the quarterly earnings announcements via learning the actual figures. Most importantly, I find that the impact of negative earnings surprises on stock returns among younger companies is significantly higher than that of positive surprises, but this differential declines with company's aging. Furthermore, this phenomenon is strongest in the subsample of the smallest companies. Overall, my findings confirm that the higher responsiveness to negative earnings news arises from the higher level of uncertainty about stock profitability, consistent with my expectations.

Second focus of this research is to discover who primarily overreacts to negative earnings surprises of growth stocks. Finding an answer to this question resolves vagueness caused by contradictory intuitions drawn from the results of various studies on this topic. So far, reactions to quarterly earnings announcements of growth/value firms from the perspective of an investor class have not been directly investigated within the sphere of the financial research.

In the work of Lakonishok et al. (1994), authors assume that the stock market overreaction to good or bad news is caused by naïve investors who become overly excited about stocks that have done very well and overly disappointed about those that have done very badly in the past. While the common notion of financial researchers is that naïve investors are equated with individuals, Lakonishok et al. (1994) argue that both individual and institutional investors are liable to engage in naïve strategies. According to La Porta (1996) and Dechow and Sloan (1997), an important feature of these "naïve" investors is that they form erroneous expectations because of the uncritical reliance on analysts' forecasts, so called *naïve expectation formation*. However, the idea underlying *naïve expectation formation* is at odds with the research of Walther (1997). The latter author shows that reliance on analysts' predictions increases with the level of investor's sophistication, thus not vice versa.

Further insights about investor reactions to negative earnings surprises of growth stocks come from studies examining investor behavior in the response to the universe of earnings announcements and other attention-grabbing events, such as Bernard and Thomas (1989), Lee (1992), Bartov et al. (2000), Ke and Ramalingegowda (2005), Barber and Odean (2008), Hirshleifer et al. (2008), Campbell et al. (2009), and Kaniel et al. (2012). The results of this research generally indicate that around earnings announcements institutional investors are momentum traders, whereas individual investors are either contrarian-to-momentum traders or net buyers for both positive and negative news.

Since I believe that the higher impact of negative surprises on the stock returns of growth companies stems from the uncertainty about their future profitability, I should be able to predict which investor class is more responsive to the negative earnings news by examining the ability to learn displayed by each of such investor classes. Evidence from past financial literature implies that institutional investors have the edge over individuals in learning about stocks' true profitability (see e.g. Odean, 1998; Barber and Odean, 2000; Grinblatt and Keloharju, 2000; Chakravarty, 2001; O'Connell and Teo, 2009). However, results from the studies of Nicolosi et al. (2009) and Seru et al. (2010) indicate that individuals also learn how to execute profitable trades, although at a relatively slow pace.

Combining all the gathered knowledge about investors' behavior, I hypothesize that institutional investors are the investor class primarily more responsive to the earnings surprises (especially those negative) of growth/young stocks in the direction of the surprise sign. Moreover, although the impact of individual trades on driving the return differential is on average negligible, I expect it to increase as individuals gain more experience. I test these predictions by examining investment patterns of institutional and individual investors with the use of the buy-sell imbalances (*BSI*) ratio. My sample consists of trading records of the households that had opened an account at a large discount brokerage firm operating in the US in the period 1991–1996, as well as of data on quarterly changes in the institutional common stock holdings reported in the Securities and Exchange Commission's (SEC) Form 13F for the same years.

As expected, the results of my tests indicate that institutional investors are indeed the investor group that tends to overreact to the earnings surprises of stocks bearing more uncertainty about their future profitability in the direction of such surprises. On the other hand, individual investors display the opposite behavior. Furthermore, my analysis also confirms that institutional investors learn about stocks' true profitability at the time of earnings announcements: the differential between *BSI* related to positive news and that related to negative news decreases with company's aging. No such pattern is observed in the individual investor trades. I also find very weak, if any, support for the view that individual investors become more responsive to the earnings surprises of young/growth firms in the direction of the surprise sign as they gain more experience. Overall, these results are in line with the learning perspective: institutional investors seem to overreact more to negative earnings surprises when they are faced with a higher level of uncertainty about the actual profitability of the corresponding firms. As they learn more on the stock true profitability during successive earnings announcements, their reactions become milder. Thus, this finding explains what is the source of the asymmetry in the magnitudes of overreaction to the unexpected earnings surprises for different stock categories.

Results of my study provide new insights into the research on growth and value stocks, investor behavior around earnings announcements and investor learning. Contrary to Lakonishok et al. (1994), I find no evidence that investors overreacting to good/bad news are naïve. Instead, results of my analyses suggest that such investors are sophisticated and well informed. Moreover, building on Pástor and Veronesi (2003), I find that the return differential between growth and value stocks appears to stem from the resolution of uncertainty about stocks' true profitability rather than from the naivety of investors.

The remainder of this thesis is organized as follows: Chapter 2 contains the literature review. Chapter 3 presents the empirical predictions together with their motivations. Chapter 4 describes the methodology and the research design. Chapter 5 discusses the data sources and the data selection. Chapter 6 examines the hypotheses and discusses results. Chapter 7 concludes.

Chapter 2

Literature Survey and Review

Three ensembles of financial literature rise to prominence regarding the domain of this work: the relationship between stock prices & earnings surprises of growth (glamour) and value companies, learning in finance, and the behavioral differences of institutional and individual investors in conjunction with the two former ensembles.

Work covered in the first part of my literature survey investigates differences in characteristics of growth & value stocks, in particular, their differential stock price reactions around quarterly earnings announcements. The second part focuses on finding effects of Bayesian Learning on investors' beliefs and outlooks – particularly, when they estimate the profitability of a company. Finally, the last two parts of this chapter examine behavior of institutional & individual investors from the perspective of their learning about stock profitability and their reactions to earnings surprises.

Theories derived from the presented three domains would be of relevance while I try to explain why do stock prices of growth firms are more responsive to the earnings surprises, in particular to those that are negative.

2.1 Earnings Surprises for Growth (Glamour) and Value Stocks

One of the topics that have drawn a lot of attention of financial researchers concerns the differences in performance between growth and value stocks. Under the typology of Lakonishok et al. (1994), *growth (glamour) stocks* are those that have displayed an excellent performance in the past and are expected by the market to continue the winning streak. Conversely, *value stocks* are the ones characterized by poor performance in the past and that are expected to perform badly in the future. Results of various financial studies have shown that pursuing value strategies (i.e. selling glamour stocks and buying value stocks) yields significantly higher average returns than performing trades in the opposite directions. While Fama and French (1992) argue that value stocks are fundamentally riskier, the evidence from Lakonishok et al. (1994), La Porta (1996), Dechow and Sloan (1997), and La Porta et al. (1997) undermines such explanation as a reason for their higher performance. Contrarily, the value stocks result to bear no more risk than the glamour stocks do. Furthermore, Lakonishok et al. (1994) believe that the inferior returns to the glamour strategies are attributed to the naivety of investors who treat the historical stock data as an indication for the future growth, assuming that this performance will persist for many years. According to these authors, such an investors' expectation, manifested by the excessive optimism about the stocks that have done outstandingly and by the excessive pessimism about those that have done very badly, leads to the overestimation of growth stocks and to the underestimation of value stocks.

The theory of the past earnings growth being extrapolated too remotely into the future as a source of the return differential between glamour and value stocks has been challenged by La Porta (1996) and Dechow and Sloan (1997). This group of authors claims that persistent errors in expectations of the future earnings growth are caused by the investors' naïve reliance on the analysts' biased forecasts rather than by the investors' inherent misperception and extrapolation. The authors demonstrate that stock prices indeed reflect the analysts' predictions, which tend to be on average imprecise or even erroneous, as around quarterly earnings announcements, stock returns experience sharp revisions of these expectations in the direction and the magnitude of the forecast errors. In particular, the earnings growth expectations are overly optimistic for glamour stocks since they display more frequent and greater negative forecast errors and their post-event returns are on average negative. Moreover, La Porta (1996) observes that, while the earnings expectations for glamour stocks experience a sharp decline of approximately 40 percent over one year, the forecasts for value stocks remain virtually unchanged. Although the difference in returns between glamour and value portfolios is significant, it systematically decreases over the subsequent years (i.e. from 21 to 6 percent over 5 years after the portfolio formation). Overall, the authors of both financial studies find mixed or no evidence of naïve extrapolation of past performance. Dechow and Sloan (1997) reject this theory, arguing that inherent overoptimistic expectations would arise from the continued increase in the growth for glamour stocks and from the continued decline in the growth for value stocks, while the actual data presents the reverse tendencies.

Returns for value and growth stocks around earnings announcements are further investigated by La Porta et al. (1997). The results of this study are consistent with the findings of La Porta (1996) and Dechow and Sloan (1997). The returns on earnings announcement tend to be significantly more positive for the value stocks than for the glamour stocks, leading to approximately 25 percent of the annual differential between these two classes of stocks. This evidence supports the notion that investors revise their expectations about stock prospects at the time of earnings announcements through learning the actual figures. Although returns of glamour stocks are on average negative, investors seem to be more surprised by good news about value stocks than by bad news about glamour stocks, as the absolute magnitude of returns is systematically greater for the value portfolio. Furthermore, the updates in expectations about value stocks appear to proceede more slowly. What is interesting is that the gap in returns between the two classes of stocks is smaller in the subsample of the largest firms, which may be justified by greater coverage in the media received by these companies. Since there is less uncertainty about the performance of these firms, the surprises are less prominent. However, the authors document that the return difference arisen at the time of earnings announcements perishes faster than the annual return gap, which undermines the hypothesis of earnings announcements being the only source accountable for the expectational revisions and the differential returns between glamour and value stocks.

One would assume that the expectational revisions result in different magnitudes of the response depending on the outcomes compared to the previous expectations. An earnings surprise occurring in the direction unexpected for a particular stock class should have more impact on the stock price than the one occurring in the congruous direction since in such a case investors deal with the dual astonishment – regarding the surprise itself as well as its type. Therefore, as glamour stocks are believed to continue to perform well, any negative earnings surprise should have a stronger effect on their returns than a positive one. Reverse should hold for value stocks – since investors assume that the unfavorable prospects of these stocks will persist, they ought to be more surprised by the positive earnings news than by the negative ones. Such hypotheses are tested and confirmed by Dreman and Berry (1995). Favorable news result to exert a significant impact on value stocks' returns and have a minor effect on growth stocks' returns. Conversely, negative surprises affect notably growth companies and have a negligible impact on value firms.

However, the substantial effect of earnings surprises on stock returns is observable only in the two extreme quintiles of the tested stocks (of the highest and of the lowest growth), while in the middle quintiles the impact is unremarkable, as such stocks are not subjected to the significant forecast errors. Moreover, as the number of positive and negative surprises is shown to be equitably distributed along the extreme quintiles and as the negligible differences in numbers are not statistically significant, the authors exclude the possibility of analysts systematically misforecasting any of the stock classes (contrary to the evidence from La Porta, 1996; Dechow and Sloan, 1997). If anything, one would expect growth stocks to outperform value stocks, given that the size of positive earnings surprises is on average significantly higher for glamour stocks, while the difference in magnitudes of negative surprises is insignificant for both stock classes. Nonetheless all of that, the overall impact of expectation corrections on the earnings announcement response tends to be slightly greater for positive news regarding value stocks than for negative information about growth stocks, as the absolute value of the average return in the surprise quarter is higher in the former case (20,05 vs -18,49 percent).

While the research of Dreman and Berry (1995) implies that responses to the adverse earnings announcements are rather symmetrically pronounced for value and growth stocks, Skinner and Sloan (2002) assume that the differential stock prices reactions to adverse surprises are concentrated only in the glamour stock class when negative news are announced. The latter authors argue that such a significantly strong response to negative earnings announcements is entirely accountable for the overall underperformance of glamour stocks. Indeed, the evidence from their study demonstrates a clear trend within the abnormal returns of firms reporting negative earnings surprises, whereas no such pattern is observable in case of positive and zero surprises. In this regard, the average abnormal returns for the firms announcing unfavorable news systematically decline as their growth rate increases, ranging from -3,57 percent for the quintile of the lowest growth to -7,32 percent for the portfolio of the highest growth. This implies that the responsiveness of stock prices to earnings surprises is subjected to the function of growth – being most pronounced among glamour firms and having the lesser impact on value firms. Moreover, stock returns result to be correlated with the sign of earnings forecast errors: the impact of negative surprises on stock prices is approximately is five-fold higher than the impact of positive earnings news. As these properties increase in growth, the study provides strong support for the hypotheses of the authors.

Skinner and Sloan (2002) argue that such a prominent asymmetric reaction to negative earnings surprises of glamour firms stems from the downward revision of investors' overoptimistic expectations about future performance of these stocks that takes place during the quarterly earnings announcements, which is in line with Lakonishok et al. (1994). Although evidence from La Porta et al. (1997) discredits the notion that learning about stock's prospects during the earnings announcements is the main cause of the return differential between two classes of stocks, Skinner and Sloan (2002) provide a solid proof supporting this concept by virtue of taking into account the possibility of earnings preannouncements. As it has been affirmed by many financial researchers, a significant number of glamour companies tend to announce negative news relatively early in order to avoid prominent stock price declines on the proper earnings announcement dates. While indeed a relatively small fraction of the glamour/value return differential is detectable on the official earnings announcement days, 80 percent of such differential is concentrated in 31 days preceding the formal news release. These results provide strong support for the notion, that the return differential between glamour and value stocks arises due to the asymmetric responses to negative earnings announcements.

On the basis of the results of Skinner and Sloan (2002), one would wonder why investors react unevenly to the forecast errors across various growth levels of stocks. In particular, one would ask why the asymmetric responses for the incongruous earnings surprises increase in significance for the high growth portfolios instead of following the logic from Dreman and Berry (1995). An important guidance for the solution to this dilemma comes from the studies of La Porta (1996) and Dechow and Sloan (1997). As mentioned already, analysts' forecasts of growth stocks exhibit a stronger inclination to be erroneous – particularly overoptimistic. Hence, it appears natural that glamour stocks, that result to be subjected to the larger expectation errors, would display larger subsequent amendments of their stock prices. However, the detailed analysis of Skinner and Sloan (2002) reveals that it is not the magnitude of forecast errors that matters for the investors in case of growth stocks, but rather the fact of the disappointment itself. For this reason, the phenomenon of the higher responsiveness to the earnings news among glamour stocks leaves an unanswered question. What also remains unclear is the source of the higher probability of forecast errors in the class of high growth companies. In order to clarify these issues, one should take a closer look at the domain of learning in finance.

2.2 Learning in Finance

Parameter estimation and learning are the concepts that are widely prevalent in finance. Agents (individuals, corporate entities, institutions), in most cases, learn about the parameters governing financial markets by analyzing large quantities of observed data as they are not certain about many of these variables due to the high degree of randomness existing in the markets.

Bayes' rule and Bayesian updating are pillars of learning in financial markets, giving us valuable insights on how agents revise their expectations after being exposed to new observations.

If we assume a parameter θ we are uncertain about and denote our belief about θ to be $\mathcal{N}(\theta_0, \sigma_0^2)$, following observing N signals about θ, $s_i = \theta + e_i$ where error term $e_i \approx \mathcal{N}(0, \sigma^2)$, our revised expectation about θ will be $\mathcal{N}(\tilde{\theta}_N, \tilde{\sigma}_N^2)$ where

$$\tilde{\theta}_K = \theta_0 \frac{\frac{1}{\sigma_0^2}}{\frac{1}{\sigma_0^2} + \frac{N}{\sigma^2}} + \bar{s} \frac{\frac{N}{\sigma^2}}{\frac{1}{\sigma_0^2} + \frac{N}{\sigma^2}} \tag{2.1}$$

$$\tilde{\sigma}_N = \sqrt{\frac{1}{\frac{1}{\sigma_0^2} + \frac{N}{\sigma^2}}} \tag{2.2}$$

where $\tilde{s} = \frac{1}{N} \sum_{i=1}^{N} s_i$ is the expected value of the signal s.

We see from equation 2.2 that not only the revised variance does not depend on observations but also as the number of observations N increases, revised variance of our parameter θ decreases, showing us that as we learn about a parameter using new observations, our uncertainty about that parameter will drop.

Formulating equations 2.1 and 2.2 recursively where $\Delta\tilde{\theta}_i = \tilde{\theta}_i - \tilde{\theta}_{i-1}$ we end up with

$$\Delta\tilde{\theta}_i = m_i(s_i - \tilde{\theta}_{i-1}) \text{ with } m_t = \frac{1}{1 + \sigma^2/\tilde{\sigma}^2_{i-1}} \tag{2.3}$$

giving us the intuition that direction of the update depends on the difference between the observed signal and the previous expectation and that magnitude of the update depends on the ratio of current uncertainty $\tilde{\sigma}^2_{i-1}$ and the observation variance σ.

One of the fields of finance where learning is applied is the stock valuation problem. As uncertainty decreases with time by learning, following 2.2, Pástor and Veronesi (2003) demonstrate that *the market-to-book ratio* (henceforth *M/B ratio*, see par. 2.2.1) declines with age over a firm's life cycle, with older firms having lower *M/B ratios* than their younger counterparts.

2.2.1 Learning about Stock Profitability during Earnings Announcements

A measure of the growth/value characteristic that has been widely used in the financial research is *M/B ratio*. The essence of this ratio is the relation between the investors' perception of the firm's value, manifested as *market value*, and the firm's value imposed by the accounting data basing on the fair, historical costs and proceeds – so called *book value*. When the market participants believe that a particular company has great prospects for the future (i.e. its future profitability is expected to be high), its market value tends to be relatively high compared to its book value. Thereby, glamour stocks (the business outlook of which is considered to be outstanding) are identified with high values of *M/B ratio*, whereas value stocks (that are expected to perform poorly) are associated with low *M/B* values.

Another interpretation of divergent values of *M/B ratio* assumes the existence of mispricing in the stock market. Consequently, the securities of a company with *M/B* above 1 are considered to be overpriced, while the ones with *M/B* below 1 are believed to be underpriced. The two presented standpoints tend to be strongly interconnected, rather than mutually exclusive, since the revisions of beliefs about the firms' growth prospects reveal that a significant fraction of glamour stocks is indeed overvalued, whereas many value companies are undervalued.

One of the patterns widely observed in the stock market is that newly listed firms tend to have disproportionately high M/B *ratios*. In particular, during the last two decades of 19^{th} century, market value of more than 10 percent of newly listed firms exceeded their book value approximately 7 times, while in 2 percent of such firms, market value was more than 20 times larger than their book value. Pástor and Veronesi (2003) argue that this phenomenon arises due to the high uncertainty about future profitability of new firms. The authors predict that the resolution of this uncertainty via learning about the actual profitability will favor a decrease in the valuation ratios, such as M/B. Therefore, a young firm facing a higher level of uncertainty about its prospects should have a higher M/B *ratio* than otherwise identical older firms, the future outlook of which is already stable.

In order to capture the evolution of learning about the mean profitability, in their empirical analysis Pástor and Veronesi (2003) use the age of the firms as a proxy for the uncertainty. While general data uncovers a continuous decline in the median M/B values over the first 10 years of the firm's life (ranging from 2,25 to 1,25), the median level of true profitability, measured via return on equity, remains generally unchanged (oscillating around 11 percent). These results imply that, while the uncertainty about profitability is subjected to dynamic modifications, firm's profitability itself is rather an undeviating metric. Further analysis reveals:

- ▷ a significantly negative cross-sectional interdependence between M/B *ratio* and the company age;
- ▷ a faster pace of M/B *ratio* decline for younger firms;
- ▷ a negative correlation between M/B magnitude and the firm size/leverage;
- ▷ an increase in these effects among the firms that pay no dividends.

Moreover, not only does M/B *ratio* decline over the course of aging of a company, but also the company's idiosyncratic return volatility declines. As the idiosyncratic return volatility is predicted to increase with uncertainty regarding the firm's mean profitability, the resulting correlation between M/B and the return volatility provides a robust proof that M/B *ratio* is an excellent proxy for the uncertainty about the average profitability of a company, in lieu of the firm age. Overall, all these findings confirm the assumptions of the learning model.

On the basis of the obtained results, Pástor and Veronesi (2003) argue that it is highly probable that overoptimistic valuations of young firms arise due to the investors' learning about stocks' prospects, rather than the investors' irrationality. Such a view poses a major implication for the study on the growth/value differential. Although the evidence from Skinner and Sloan (2002) supports the notion that learning about the actual firm's performance during earnings announcements favors the variation in the returns of two classes of stocks, scholars remain silent about the source of *the one-sided asymmetry in the magnitudes of overreaction to unexpected earnings surprises for different stock categories* (henceforth *AMOUES*). Precisely, it remains unclear why the disappointment following the excessive optimism about growth stocks causes greater effects on the stock returns than the elation following the excessive pessimism about value stocks.

In the light of the findings of Pástor and Veronesi (2003), I assume that the higher level of responsiveness to the earnings news (especially those negative) and the higher probability of forecast errors that occurs among the growth (glamour) stocks is attributable to the higher level of uncertainty about these stocks. As the firms age, their responsiveness to the quarterly earnings news decreases together with the likelihood of forecast errors since the uncertainty about their profitability becomes resolved via learning.

My assumption seems to be consistent with discoveries of other financial studies on earnings expectations. In particular, the steep declines in expectations of glamour stocks' performance and the static pattern for value stocks reported by La Porta (1996) appear to confirm the finding that the uncertainty declines at a faster pace for the stocks with higher *M/B ratios.* Additionally, the observed by La Porta et al. (1997) smaller return differential between these two classes of stocks is the subsample of the largest firms seems to be explained by a lower level of uncertainty that investors encounter while assessing the profitability of these firms. Conversely, the finding of Brown et al. (1987), which implies that the accuracy of analysts' forecasts increases with the firm size, is in line with the result of Pástor and Veronesi (2003) that smaller firms are in general associated with higher uncertainty about the mean profitability.

2.3 Learning about Stock Profitability among Individual and Institutional Investors

When discussing learning about stock profitability, it is worth to consider behavioral disparities between institutional and individual investors. Based on the different levels of sophistication and trading experience, if anything, one can expect an uneven pace of learning and divergent reactions to the earnings announcements of each group. According to the assumption of Bartov et al. (2000), stock returns around the earnings announcements reflect a weighted average of all investors' expectations in regard to the company value. In the light of this premise, the influence of individuals on the financial markets should not be neglected, as they hold nearly a half of the common stock in the financial market (see Hirshleifer et al., 2008).

Many studies demonstrate that individuals on average are not particularly good traders. What is more, their actions frequently seem to be deprived of rationality and, instead, to be driven by emotions. Lee et al. (1991) equate individual investors with noise traders. Barber and Odean (2000) document that the aforementioned group performs rather unremarkably: after inclusion of the transaction costs, their abnormal returns tend to be even negative. What is the most striking is that, the more active the traders become, the lower abnormal returns they obtain. These results would suggest that individual investors do not improve their trade skill with the investment experience. Odean (1998) examines whether the individual investors are prone to *the disposition effect*[1]. The author finds strong support for this tendency, as individuals do sell their winners more readily than their losers throughout a year, with an exception for December (when traders are tax-motivated to dispose of losers). Odean (1998) provides evidence that propensity for disposition effect cannot be justified by rational motivations, such as willingness to rebalance portfolio or avoidance of paying higher transaction costs. Furthermore, the author indicates that it is futile to await the mean-reversion, as former winners that were sold tend to significantly outperform losers that are still held in the portfolio. The tendency for the disposition effect is therefore detrimental to the trading profitability.

[1]The disposition effect is the propensity to hold the losing stocks too long and to sell the winning stocks too soon, first labeled with this term by Shefrin and Statman (1985).

Summers and Duxbury (2012) believe that the disposition effect is driven by the emotions anticipated by individual investors during the trading activity. Since selling a stock for a loss leads to a strong negative sensation of disappointment and regret, the extended period of holding a position for a loss can be explained by the investor's desire to avoid these feelings and the hope that the stock will rebound. The authors argue that the existence of an emotional commitment to trading is a sufficient factor for creating the disposition effect. The notion of the influence of emotions on trading choices is also developed by Strahilevitz et al. (2011). The authors propose that, as time goes by, individual investors engage themselves in activities that induced pleasure during the earlier trades and avoid ones that triggered pain. To confirm this point, Strahilevitz et al. (2011) measure investors' willingness to repurchase previously owned stocks through analyzing trading records of individual investors obtained from a large discount brokerage firm and from a large retail broker. In line with their expectations, they find evidence that individual investors are significantly less likely to reacquire (a) stocks that were formerly sold for a loss rather than stocks formerly sold for a gain, and (b) stocks previously sold for a gain, whose price has increased since their sale compared to stocks whose price has dropped. What is interesting is that these tendencies are more pronounced for the dataset from the large discount brokerage firm, whose clients are constrained to be self-reliant, than for the data from the retail brokerage firm, whose clients are wealthier and can benefit from advice of a broker. These results would therefore suggest that trades of individual investors are prone to be driven by emotions, but the presence of an experienced adviser attenuates this propensity.

Indeed, on the other hand, institutional investors are regarded as "smart" and rational traders, who due to their sophistication possess the ability to correctly analyze and interpret factors influencing stock returns. The study of Chakravarty (2001) reveals that the majority of medium-size trades that display the largest impact on stock prices are initiated by institutional traders. This finding thereby supports a common notion of institutions being informed investors. O'Connell and Teo (2009) investigate the behavior of large institutional funds faced with gains and losses. They find that, unlike individual traders, the above-mentioned group is rather not susceptible to the disposition effect: given even a slightest loss, institutions tend to immediately withdraw from the investment, while in the aftermath of profits they display an inclination to increase the risk and to ride such gains. However, the short-lived funds increase the risk following gains more aggressively than the long-lived ones do, which proves that the overreaction to gains weakens with age and experience. Overall, the strategies undertaken by institutional investors lead them to achieve significantly positive returns, as opposed to the performance of an average individual investor.

The explicit propensity for the adverse behavior between various categories of investors was captured in the study of Grinblatt and Keloharju (2000). Its dataset consists of stock trades of all the participants operating simultaneously in the Finnish stock market, thus both retail (households) and institutional (nonprofit institutions, general government, finance & insurance institutions, non-financial corporations and foreign investors) traders. The authors find that an enhancement in the investor's sophistication monotonically increases the tendency for the momentum behavior (i.e. acquiring past winners and selling past losers) and vice versa. That is, foreign investors (composed mainly of investment banks and professionally managed funds) tend to pursue momentum strategies, whereas Finnish household (considered as the least sophisticated traders) are prone to the contrarian behavior – buying past losers and disposing of past winners. Moreover, foreign investors attain on average superior performance, while households are characterized by significantly negative returns. These patterns are consistent with findings of Odean (1998), Barber and Odean (2000), and O'Connell and Teo (2009) and persist even over longer horizons, proving not to be a product of a chance. On the other hand, Finnish institutional investors (which are less sophisticated than foreign investors but more sophisticated than households) exhibit investment strategy and investment performance in between those of the two aforementioned groups.

The concept of individuals being irrational traders has been repeatedly challenged for the recent years. Schmeling (2007), likewise, uses a dataset jointly covering individuals and institutions. His study surveys stock movement expectations of investors in Europe, the USA and Japan over five consecutive years. The author expects, inter alia, the individual investors' sentiment to predict stock market returns erroneously, whereas the institutional sentiment to forecast them correctly at intermediate and long horizons. Furthermore, the author assumes the shifts in individual and institutional sentiment to be negatively correlated in the long term. The results confirm that, on average, institutional investors' sentiment does correctly anticipate long-term excess returns in all the five stock markets and that institutional investors systematically adjust their sentiment downwards (upwards) when they expect individual sentiment to be high (low). On the other hand, the study proves that individual sentiment fails to correctly predict future stock movements and that individuals do not incorporate the expected institutional sentiment into their forecasts, which confirms that they may be seen as proxy for noise trader risk, consistent with Lee et al. (1991). However, strikingly, the evolution of individual sentiment reveals the clear evidence of structural change, especially in European markets. Towards the end of the sample, the individuals' expectation is no longer subjected to the statistically significant negative future returns, while the institutional sentiment is still able to predict the excess returns correctly. Likewise, while in the beginning being inversely correlated, these two sentiment indices start to match pattern as we move forward in the sample. The author argues that a potential reason for this unusual finding could be the time needed by individual investors to learn about predicting power of institutional investors for future stock returns. However, the results for individual investors are strong only in the US and European markets, whereas in Japan the positive correlation between two sentiments appears to be strong throughout the entire sample.

Feng and Seasholes (2005) investigate whether the propensity for the disposition effect can be attenuated throughout the development of investor's sophistication and the acquisition of trading experience. Using an indicator of portfolio diversification on the first day of investment career, number of trading rights, gender and age as proxies for the level of sophistication, as well as cumulative number of taken positions as a proxy for the experience, the authors examine the evolution of investors' behavior in the People's Republic of China since the inception of their trading activity. The results reveal that, when tested separately, an increase both in sophistication and in experience significantly attenuates the hesitance in selling past losers and somewhat reduces the tendency for selling past winners. However, when sophistication and experience are combined and analyzed jointly, the disposition effect is totally eliminated with respect to losses and significantly diminished in the region of gains. These discoveries prove, that the irrational behavior of individual investors is not persistent over time and suggest that they do possess the ability to learn.

Nicolosi et al. (2009) and Seru et al. (2010) empirically examine whether individual investors display any of the two types of learning recognized by scholars – "learning about ability" and "learning-by-doing". The first type is based on the learning model by Mahani and Bernhardt (2007) which assumes that individuals are predestined to either possess the profitable trading ability or to be permanently unskilled. Although only a low fraction of the population falls into the former group, none of the agents knows their category at the beginning of their trading activity. However, over time they revise their belief about their financial skills by observing their previously-demonstrated portfolio performance and, on the basis of this feedback, decide whether to quit the stock market or to stay in and intensify their transactions.

Second type of learning builds on the intuition from the model of Grossman et al. (1977) and hypothesizes that agents are able to improve their trading skills through experience. Nicolosi et al. (2009) discover that, while individual traders, on average, fail to correctly foresee positive future returns, the fraction of profitable transactions and the trade intensity do nonetheless increase as investors are able to extrapolate their superior trading skills from the past outcomes. Furthermore, the study also provides an evidence that investment performance becomes significantly more successful with gaining experience. Seru et al. (2010) come to similar results, i.e. that trade effectiveness of individual investors increases both via investment experience and via learning about financial skills. The authors deliver also strong support for the attenuation of the disposition effect by experience, consistent with findings of Feng and Seasholes (2005). However, Seru et al. (2010) indicate that investors learn rather slowly via "learning-by-doing". Based on the results of the survival analysis, the authors identify "learning about ability" to be the primary source of individual investor learning, as the substantial fraction of individuals abandon their investment career relatively early.

The results of the studies on the investor learning that are presented here, constitute a point of departure for the further analysis. Examination of the actual financial data from the separate investor groups' perspective may shed more light on their role in learning about stock profitability.

2.4 Earnings Surprises Reactions among Various Investor Types

One would wonder which investor class is more prone to cause the return differential between glamour and value stocks. According to the notion of learning about stock profitability as a driver of the return differential and the evidence presented in the previous section, it appears that institutional investors are such a group, as they learn at a faster pace than individuals. However, Lakonishok et al. (1994) suggest that the underperformance of glamour stocks and the overperformance of value stocks is the effect of naivety of investors who anchor their beliefs about the future earnings performance of a given company based on a series of past news regarding its earnings growth. These naïve investors buy a large amount of high growth stocks since they are led by the overoptimism about such stocks' future earnings prospects. Conversely, they sell on a large scale low growth stocks, motivated by the overpesimism about their future earnings growth. An important assumption of the aforementioned authors is that naïve investors persist in their trading strategies for a long time, and hence gain low returns. Panel A of Figure 2.1 depicts a scheme of the cause-and-effect process leading to the return differential according to Lakonishok et al. (1994).

While the theory of Lakonishok et al. (1994) implies that investors following "naïve" strategies do not appear to be aware of the mispricing that arises due to their trades, and hence continue investing in the same way, the evidence from Skinner and Sloan (2002) tells us a different story. The cause-and-effect process leading to the return differential in line with findings of the latter authors is depicted in Panel B of Figure 2.1. As we see on the scheme, earnings announcements constitute a key turning point in the investors' beliefs about stocks' future performance. According to Skinner and Sloan (2002), the return differential between glamour and value stocks stems mainly from the overoptimism about the former class of stocks. If an earnings surprise is negative, the market value of the relevant company declines dramatically. The same investors, who were previously overly excited about high growth stocks, become now overly disappointed about those reporting negative news.

So far, the aforementioned studies imply that the group of investors causing the return differential between growth and value stocks is naïve and/or prone to

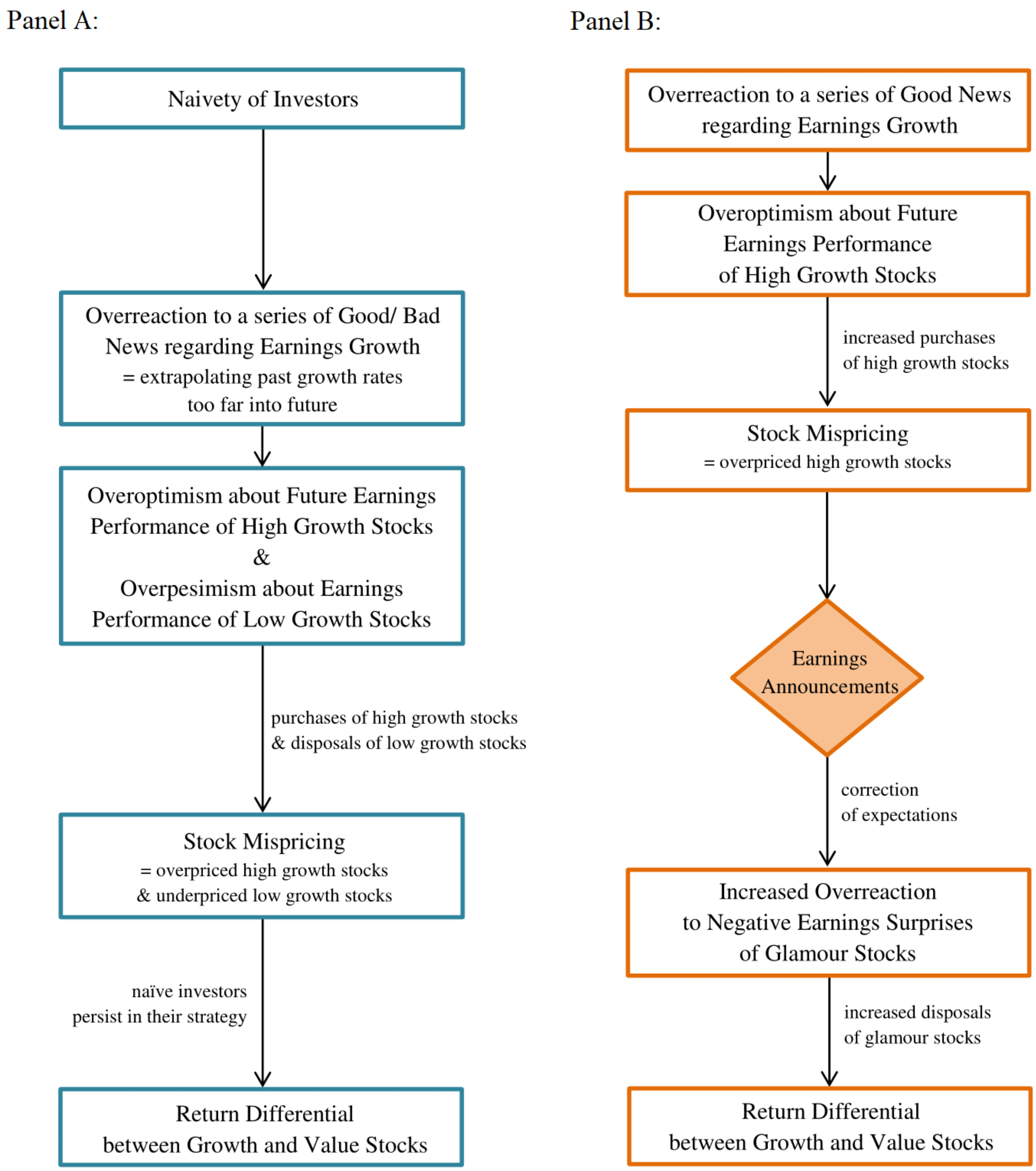

Figure 2.1: Cause-and-Effect Process Leading to the Return Differential between Growth and Value Stocks, according to Lakonishok et al. (1994) and Skinner and Sloan (2002)

The figure presents schemes of the cause-and-affect process leading to the return differential between growth (glamour) and value stocks. The scheme in Panel A is created based on the work of Lakonishok et al. (1994), whereas that in Panel B is created based on the research of Skinner and Sloan (2002).

overreact. Another important feature that emerges from the research of La Porta (1996), Dechow and Sloan (1997), and Skinner and Sloan (2002) is that this investor group follows analysts' forecasts.

Evidence from the studies of Summers and Duxbury (2012) and Strahilevitz et al. (2011) leads to the surmise that the return differential may be induced by individual investors, as this group appears to be particularly driven by emotions, and hence is susceptible to react excessively. Also, the research of Barber and Odean (2000) seems to confirm this notion: similarly to the followers of "naïve" strategies, individuals perform poorly on the stock market. On the other hand, the mere theory of the disposition effect excludes the possibility of overreaction to negative news through increased disposals of a relevant stock. Precisely, findings of Odean (1998) and Grinblatt and Keloharju (2000) show that individuals do not sell losers immediately after negative news, whereas such a pattern is displayed by investors overreacting to earnings surprises. However, Lakonishok et al. (1994) suggest that glamour strategies triggering the stock market overreaction to earnings news are undertaken by both individual and institutional investors. Individuals may act in this manner because they naïvely equate well-run companies with "good investments" and therefore expect their winning streak to persist. On the other hand, institutions may tilt towards glamour strategies due to the career concerns of money managers who want their investments to appear flawless in the eyes of their clientéle. These ambiguous conjectures call for a detailed analysis of the literature on investor behavior following the earnings announcements.

2.4.1 Earnings Surprises Reactions of Individual Investors

Financial research of the last three decades has found several non-homogeneous patterns in the post-earnings announcement behavior of the individual investors. Scholars are also not able to agree on the motives underlying the trade directions of individuals – ranging them from being completely random to perfectly aligned.

If perceived as "naïve investors", individuals may be identified as the source of *the post-earnings announcement drift* (henceforth *PEAD*)[2]. Such an implication stems from the study of Bernard and Thomas (1989) who suggest that uninformed

[2] *PEAD* is the tendency for the stock's cumulative abnormal returns to drift in the direction of an earnings surprise for several weeks (or even months) following an earnings announcement.

and uncertain investors are the ones who bear the responsibility for causing $PEAD$, as they fail to incorporate the available information into their trading decisions. The authors also prove that $PEAD$ is stronger among shares of smaller companies, which further supports the presented notion[3]. Additionally, the study of Bartov et al. (2000) reveals that $PEAD$ is mostly pronounced for the companies with the highest level of individual investor ownership. Given all that, one would expect the individuals to trade in the directions opposing a rational stock price adjustment, hence to sell the stocks that experience positive earnings surprises and to buy the ones that experience negative surprises. This expectation overlaps with the actual results from the studies of Grinblatt and Keloharju (2000), Kaniel et al. (2008), and Kaniel et al. (2012). Such trades delay the adjustment of price to the current earnings information, and thereby provide a counter-argument to the hypothesis that individuals are responsible for the overreaction to the earnings announcements.

The most meaningful evidence of individual traders causing $PEAD$ comes from the study of Kaniel et al. (2012). The authors show that individuals not only intensively buy following bad news and sell following good news on and after the earnings announcements dates, but they also actively trade prior to these events. The pre-event trading mostly consists of buying stocks that will experience favorable earnings surprises and of selling ones that will experience unfavorable surprises. Kaniel et al. (2012) conjecture that such a reversion of positions is not a coincidence, and hence may be intentionally conducted in order to profitably exploit private information. Indeed, the authors prove that half of the predictability of abnormal return may be attributed to superior information or a skill possessed by individual investors. However, these findings contradict the common view of individuals being irrational, naïve traders.

Second set of the studies on individual responses to the earnings announcements represents the view that individuals are the "attention-grabbing" investors, and hence, while although being naïve, they do not cause $PEAD$. Using small trades as a proxy for individual investor behavior, Lee (1992) finds that around earnings announcements small traders make an unusually large number of purchases, regardless

[3]Lee et al. (1991) indicate that the increase in firm size is negatively correlated with the percentage of the individual investor ownership – the smallest stocks are usually held by the largest share of individuals. This assertion is consistent with the evidence of Barber and Odean (2000), that average individuals favor more small stocks.

of the news type. That is, they are net buyers of stocks experiencing both positive and negative earnings surprises. Moreover, the abnormal buying of small traders is weaker and more dispersed than trades performed by large traders. The author argues that potential reason for this pattern can be the inhibited access to the relevant financial information for the individual investors, which instead triggers an inclination to buy stocks that receive sufficient media coverage irrespective of the news type. This individual indifference to the type of earnings releases may be explained by results of Walther (1997), who proves that reliance on analysts' forecasts (while forming earnings expectations) is positively correlated with the level of investor sophistication. Her finding implies that trades of the individuals (who are considered to be the least sophisticated investors) are less prone to arise in response to the irrelevant forecasts of earnings announcements, as this group simply tends to ignore such forecasts.

Campbell et al. (2009) reject the validity to use the small trades as a proxy for the individual investor behavior, arguing that small trades are rather the indication of institutional transactions. Such a point of view seemingly nullifies the conclusions of Lee (1992). However, the evidence from the studies of Barber and Odean (2008) and Hirshleifer et al. (2008) supports the notion that individuals are net buyers following all types of earnings announcements.

Barber and Odean (2008) measure the buy-sell imbalances for purchases and sales executed by three types of unsophisticated investors (clients of: a large discount brokerage, a smaller discount brokerage, and a large retail brokerage) as well as by three types of sophisticated investors (momentum managers, value managers, and diversified managers) in response to attention-grabbing stimuli. The authors find that on average, unlike the institutional investors, individuals are prone to be the net buyers of stocks that particularly drive attention. Tendency for this behavior is mostly pronounced among the least sophisticated investors from the large discount brokerage and attenuates with investor sophistication. When extreme returns are taken into account as a proxy for attention stimulus, clients of the large retail brokerage and clients of the small discount brokerage display a propensity to buy the big losers, but not to buy the big winners, which is consistent with Grinblatt and Keloharju (2000). However, when abnormal trading is used as a proxy, all the three classes of individual investors result to be net purchasers of attention-grabbing stocks.

Hirshleifer et al. (2008) analyze the actual trades made by individual investors at a large discount brokerage on the days following earnings releases. The authors divide their sample into three investor classes based on the number of trades performed during a year: actively trading investors, high-capital investors, and general investors. The results reveal that individual investors are the net purchasers after both positive and negative earnings surprises. Even after accounting for the possibility that attention-driven trades of the class of the least sophisticated investors may obscure trades in the opposite direction executed by a more sophisticated investor class, and hence affect the results, the tendency for net acquisitions remains unchanged. However, net purchases after the unfavorable surprises are on average significantly greater than after the favorable ones. Therefore, while the hypothesis about individuals hindering the upward price adjustment after good news can be rejected (because they are not net sellers after such events), there is a strong evidence that individual investors impede the downward price adjustment after unfavorable earnings surprises (as they are evident net buyers following bad news).

Although the outcomes of the presented studies provide contradicting evidence on individual investor behavior following positive earnings surprises, all of them find the same trading pattern occurring after negative earnings surprises: individuals result to be net buyers in response to the unfavorable earnings releases. One may infer that such behavior hampers the downward price adjustment. Therefore, trades of this investor group do not seem to be a source of the asymmetrical response to the negative earning surprises of growth stocks. Yet, an analysis of the behavior of the institutional investors may shed more light on this issue.

2.4.2 Earnings Surprises Reactions of Institutional Investors

Unlike in case of individual investors, financial researchers found more concurring results for the post-earnings announcement behavior of institutional investors. Lee (1992) uses large trades as a proxy for trading of institutional investors and observes that large traders respond to the positive earnings news by an intensive stock acquisition and to the negative news by an elevated stock sale. Moreover, the author reports that large trades, unlike small trades, are performed relatively quickly, being mainly concentrated in the first few hours after the news release. This evidence suggests that institutional investors are informed traders, who pursue momentum strategies, which is corroborated by the study results of Grinblatt and Keloharju (2000), Chakravarty (2001), and O'Connell and Teo (2009).

Similar conclusions about the institutional investor trading are presented by other researchers. Bartov et al. (2000) analyze the patterns in stock returns following earnings announcements in relation to the percentage of stock held by institutional traders. They observe that the magnitude of *PEAD* is negatively correlated with the proportion of institutional ownership of a stock. The authors argue that sophisticated investors (equated with institutional traders) reduce drift since they correctly decipher the actual earnings information, and hence improve the efficient stock pricing. The finding of Bartov et al. (2000) is confirmed by Ke and Ramalingegowda (2005), who additionally show that *PEAD* is mainly exploited by active institutional investors (transient institutions) and that such trading earns them significant abnormal returns. The intensive transactions of this group, performed in the direction of earnings surprises, significantly accelerate the implementation of current earnings into the stock prices. As mentioned before, Campbell et al. (2009) argue that small trades ought to be used as a proxy for institutional trading instead of proxying them for individual stock activity. Even after including jointly small and large trades into the analysis of institutional trading in the post-earnings announcement period, the authors obtain results similar to those of Lee (1992). Once more, institutional investors turn out to be the return momentum traders. Furthermore, Campbell et al. (2009) show that institutions anticipate *PEAD* through the acquisition of stocks prior to positive earnings surprises and through the sale of stocks in advance of unfavorable earnings surprises.

The behavior of different investor types following earnings announcements is further investigated by Barber and Odean (2008), who, as already mentioned, classified investors within six categories. Overall, institutional investors do not pursue attention-driven stock acquisitions regardless of the direction of the previous day's extreme returns, and are less inclined to do so on the high abnormal volume days. These results are especially valid for value-strategy managers, who intensively buy on low-volume days. It is worth to note, that each of the three categories of professional investors responds differently to the previous-day's extreme returns. Momentum managers dispose of recent losers and acquire winners. In contrast, value managers and diversified managers trade in the opposite directions, buying recent losers and selling winners. Interestingly, when comparing the professional investor activity following days with extreme returns with regard to the existence of news coverage, the return momentum strategy of momentum managers persists even without news. Nonetheless, in case of value and diversified managers, the results are mixed and inconclusive.

Overall, the above-cited research shows that institutional investors are informed traders and that they display clear trading patterns in response to the earnings announcements. These findings are consistent with Walther (1997), who reports that, the more the investors are sophisticated, the more weight they place on analysts' forecasts. One can therefore infer that professional investors are totally aware of the content of analysts' forecasts.

Three major implications for my research appear here:

- ▷ while we lack unambiguous evidence of a clear response to the sign of earnings surprises in case of individual investors, institutional investors surely react to such events since the surprises arise from the irrelevant analysts' predictions;
- ▷ as sophisticated investors place more weight on analysts' forecasts while forming their earnings expectations, they might be more prone to overreact in case of failed predictions;
- ▷ awareness of a discrepancy between forecasts and the actual earnings enables professionals to react instantly through undertaking transactions in a desired direction.

Combining these deductions with the previously elaborated conjecture that individuals trade against the downward price adjustments, one would suspect that institutional investors are the ones that drive the asymmetrical response to the negative earnings surprises related to growth stocks. However, although institutional investors as a whole are considered to be the momentum traders following earnings announcements, the evidence from Barber and Odean (2008) indicates that only a group of momentum managers behaves in this manner, while the rest trade in the opposite directions. These ambiguous conclusions call for a detailed investigation of the actual trading data.

Chapter 3

Hypotheses Formulation

In this chapter, I introduce my hypotheses, which are the key aspect of this thesis. Moreover, I discuss in detail past empirical evidence motivating their creation.

On the ground of the empirical findings presented in the literature survey part, I assume that the higher level of responsiveness to the negative earnings surprises displayed by stock returns of growth (glamour) firms, which in turn causes the return differential between growth and value stocks and *AMOUES*, is attributable to the higher level of uncertainty about the true profitability of these firms. If the resolution of uncertainty indeed fosters the decline in the responsiveness to the negative news throughout subsequent lower growth classes of stocks, I should find a similar pattern while examining responsiveness to the earnings surprises as a function of the firm age (which is a proxy for uncertainty). Therefore, I develop the following hypotheses:

1. *The impact of earnings surprises on the abnormal stock returns of a firm decreases with time due to investors' learning about firm's actual profitability.*

   In other words, I assume that growth/young stocks are characterized by larger responsiveness to the earnings news due to a higher level of uncertainty about these stocks' profitability (see Pástor and Veronesi, 2003). Investors are expected to overreact to earnings surprises more severely in case of growth/young companies due to the higher uncertainty they face and therefore stronger revisions of their previous beliefs. However, as investors learn about firm's true profitability over the course of subsequent earnings announcements, the impact of earnings surprises on stock returns should gradually decrease.

2. *Stock price responsiveness to negative news for the earnings announcements of younger companies is higher than that related to positive news, and this differential pattern decreases with company's aging due to investors' learning about company's true profitability.*

   Past financial research indicates that investors are generally overoptimistic about growth stocks since, when faced with bad news regarding these stocks, they overreact more remarkably than when faced with good news. Some authors (like Lakonishok et al., 1994) imply that such an overoptimism comes from a naïve misperception of the mere investors. Others (like La Porta, 1996; Dechow and Sloan, 1997) argue that it arises due to indiscriminate reliance on analysts' forecasts, which turn out to be erroneous especially for growth stocks. In either case, if the overoptimism stems from the uncertainty about stocks' true profitability, I expect to find a similar overreaction to negative earnings surprises of young firms. Thus, the expectational revision in case of negative news should have higher magnitude than that following positive news, which in turn should result in the higher stock price responsiveness to negative surprises among young firms. I expect this pattern to decrease throughout company's aging as investors resolve the uncertainty during the subsequent earnings announcements.

3. *The higher responsiveness to negative earnings news of younger firms is more pronounced among smaller firms.*

   It is worth recalling that La Porta et al. (1997) observed that the return differential between growth and value stocks is significantly larger in the subsamples of smaller firms. On the other hand, the results of Brown et al. (1987) suggest that the accuracy of analysts' forecasts is correlated with the firm size. These findings seem to be explained by the higher level of uncertainty that stakeholders face while assessing performance of smaller firms (see Pástor and Veronesi, 2003). The reason for this is the smaller amount of information about such companies being available to general public. These firms are also characterized by a lower number of analyst followings and by lower transparency. Conversely, large firms are associated with disproportionately high media coverage, intensive analyst followings, and hence with significantly high transparency. Therefore, if the greater impact of negative surprises on stock prices of young/growth firms indeed stems from the higher level of uncertainty, I expect to find a stronger differential impact of earnings surprises as a function of age among the smallest firms and a weaker impact among the largest companies.

4. *Among two classes of investors, institutional investors display a higher level of responsiveness to the earnings surprises of young stocks (especially to the negative news) in the direction of a surprise due to the superior ability to learn about stocks' profitability. Hence this group is primarily responsible for driving the return differential and causing AMOUES.*

   If the higher responsiveness to the negative earnings surprises of young/growth stocks and the subsequent gradual decline in this responsiveness throughout company's aging stem from the resolution of uncertainty about the true profitability of these stocks by a group of investors, one should be able to identify such a group on the basis of a set of its particular characteristics. First of all, such a group should be able to detect forecast errors and to react to them in a timely manner. Secondly, it should unambiguously be capable of learning about stock profitability. Lastly, it should display a tendency for the momentum behavior (i.e. for acquiring past winners and selling past losers) around the earnings announcements.

   As already mentioned, in general, individuals do not exhibit any significant sensitivity to the analysts' forecasts, nor are they characterized by a strong ability to learn about stocks' true prospects (see Walther, 1997; Seru et al., 2010). Furthermore, results of past financial research (e.g. Barber and Odean, 2008; Hirshleifer et al., 2008; Kaniel et al., 2012) suggest that individuals trade against the downward price adjustments and therefore they attenuate the impact of negative surprises on stock returns. On the other hand, institutional investors are characterized by substantially higher awareness of discrepancies between analysts' predictions and the actual earnings due to their propensity to possess broader knowledge about stock market figures (see Walther, 1997). Furthermore, among the two investor classes, institutions display a substantially stronger propensity for the momentum behavior (see Grinblatt and Keloharju, 2000; O'Connell and Teo, 2009). Finally, experimental evidence indicates that institutional investors react to the earnings announcements very swiftly, in general in the direction of the surprise sign (see Lee 1992; Bartov et al. 2000; Ke and Ramalingegowda 2005). Thus, the latter investor class seems to be the group primarily more responsive to the negative earnings news of young firms, which in turn leads to *AMOUES* and to the return differential between growth and value stocks.

5. *Individual investors display higher responsiveness to the earnings surprises of young/growth stocks in the direction of a surprise as they gain experience.*

   Past financial research has suggested that individual investors are able to learn about stocks' profitability and about executing lucrative trades through gaining more experience (see Nicolosi et al., 2009; Seru et al., 2010). Therefore, although individual reaction to the earnings announcements is on average tenuous, I expect that, the more individuals learn about stock market, the more explicit patterns in their behavior following the earnings announcements become. These patterns are expected to occur in the directions of earnings surprises.

In this thesis, I make several contributions over the established research within the financial literature by testing the aforementioned predictions. In particular, my hypotheses link the discrepancies in the impact of earnings surprises on stock returns directly to the function of learning about stock profitability. While Skinner and Sloan (2002) find that the return differential between glamour and value stocks arises at the time of earnings announcements due to glamour stocks displaying a substantially higher responsiveness to the negative earnings news, they do not explore the cause of it. Instead, they assume after Lakonishok et al. (1994) that the overreaction to the negative earnings surprises in case of glamour stocks stems from the expectational errors regarding these stocks. Lakonishok et al. (1994) argues that these expectational errors arise due to naivety of investors. According to Lakonishok et al. (1994), same naivety leads to the overvaluation of glamour stocks and to the undervaluation of value stocks (see Figure 2.1). On the other hand, findings of Pástor and Veronesi (2003) imply that the overvaluation of glamour stocks is caused by a higher level of uncertainty about stock profitability. Examining the asymmetrical response to the negative earnings surprises through the learning based intuition coming from Pástor and Veronesi (2003) enables me to check whether the return differential between glamour and value stocks is due to the higher level of uncertainty about profitability of relevant stocks rather than due to the investor naivety, contrary to Lakonishok et al. (1994). Hypotheses H1 – H3 directly capture the effect of learning by using the company age as a proxy for uncertainty. Hypotheses H4 and H5 examine whether the effect of learning rather than the investor naivety causes the asymmetrical response to the negative earnings news, by contrasting trades of institutional and individual investors, with the former being traditionally considered sophisticated and the latter being traditionally considered naïve. In this regard, H4 and H5 imply that the asymmetrical response is indeed a product of resolving uncertainty about stock profitability by sophisticated investors rather than a product of overreaction of naïve investors, further building the bridge between learning about stocks and the asymmetrical reactions to the earnings announcements.

Chapter 4

Methodology

This chapter, where I describe the research design, is divided into two parts. In the first section, regressions and corresponding dependent & independent variables are elaborated in order to test the validity of the first three hypotheses. I also explain how I will further analyze the regression coefficients and other assumptions that have been made and I describe the strategy I will follow if those assumptions are deemed invalid. In the second part, I present the methodology of the *BSI* (i.e. *buy-sell imbalances*) analysis that tests the last two hypotheses. Moreover, I describe the procedure on how I will evaluate the robustness of this analysis.

4.1 Methodology for Regression Analysis

4.1.1 Variables

First part of the key analysis consists of categorizing firm-quarters based on the firm age and subsequently identifying an average pattern of the stock return response to the adversarial earnings surprises for every age group. Following Pástor and Veronesi (2003), I define the AGE variable as the reciprocal of two plus the firm age[1], as in the formula below:

$$AGE = \frac{1}{2 + firm\, age} \tag{4.1}$$

[1] I modify the original specification of the AGE variable by Pástor and Veronesi (2003) (which is the reciprocal of one plus the firm age) since the aforementioned authors assume that a firm is 1 year old in the year of the Initial Public Offering (henceforth IPO), whereas I assign this age to a firm whose IPO was in the previous calendar year.

Such a construction of the *AGE* variable is in line with the assumption that uncertainty about the firm's mean profitability is being resolved over the course of firm's aging due to investors' learning. As years pass, the influence of this variable on the abnormal stock returns is expected to decrease. Therefore, *AGE* is a proxy for uncertainty.

Following Skinner and Sloan (2002), I calculate a quarterly earnings surprise as the difference between the median forecast of quarterly *earnings per share* (henceforth *EPS*) and the realized quarterly *EPS*. On the basis of this measure, I construct three variables: *SURPRISE* (equal to -1; 0; 1 if the earnings surprise is respectively: negative; absent; positive), *GOOD* (taking the value of 1 in case of a positive surprise and 0 otherwise), and *BAD* (taking the value of 1 in case of a negative surprise and 0 otherwise).

The last variable to be defined in this part of the study is the firm's buy-and-hold abnormal return ($BHAR_i$) related to the quarterly earnings surprise. It is calculated by subtracting the buy-and-hold expected return in the absence of earnings announcement from the firm's realized buy-and-hold stock return over a predefined period, as in the following formula:

$$BHAR_{i,(\tau_1,\tau_2)} = \prod_{t=\tau_1}^{\tau_2}(1+R_{i,t}) - \prod_{t=\tau_1}^{\tau_2}(1+E\left[R_{i,t}\,|\,\Omega_{i,t}\right]) \tag{4.2}$$

where

$R_{i,t}$ = the realized stock return for company i on day t;

$E\left[R_{i,t}\,|\,\Omega_{i,t}\right]$ = the expected return for company i on day t in the absence of earnings announcement.

To put it more rigorously, using the *Capital Asset Pricing Model* (*CAPM*), I calculate the expected stock return as:

$$\frac{E(R_i) - R_f}{\beta_i} = E(R_m) - R_f \tag{4.3}$$

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \tag{4.4}$$

where

R_i = the stock return for company i;

R_f = the risk-free rate;

R_m = the average daily return of the size-matched decile portfolio.

I estimate R_m by assigning the stocks to 10 (decile) portfolios based on their market capitalization at the beginning of each calendar quarter and then by calculating the mean return for each portfolio on a daily basis. Being aware that one company can issue different securities under different CUSIP numbers[2], I generate the total market value of all the securities under one company code (PERMCO) for each trading day. I obtain market capitalization by averaging total market value of a company during the first week of a calendar quarter. In case a company was not traded during the first week of a particular calendar quarter, I consider the soonest week of the same quarter when the trading records are available to be the first week of a quarter for such a company.

To be confident of the correct calculation of β coefficient, I calculate it myself over a period of 180 trading days following the event window, checking R^2 measure as a goodness-of-fit. Thus β coefficient becomes:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} = \rho_{i,m} \frac{\sigma_i}{\sigma_m} \tag{4.5}$$

As financial evidence indicates, many companies constantly pre-announce earnings and three-quarters of such pre-announcements take place within two weeks preceding the earnings announcement date. To account for this issue, Skinner and Sloan (2002) create four abnormal return measurement intervals. Since in their study the interval labeled *postret* has resulted to have particularly significant explanatory power, in this thesis I restrict my analysis solely to the aforementioned interval. To be precise, *postret* averages 33 trading days and accounts for the period beginning 12 trading days before the end of the forecast fiscal quarter and ending 1 trading day after the earnings announcement. In case a forecast period end occurs during a non-business day, in order to maintain an event window starting 12 trading days before

[2]The CUSIP (Committee on Uniform Securities Identification Procedures) number is a unique identification number ascribed to each security publicly traded in the US and Canada.

the forecast period, it is converted to the first available business day following that date. In case an earnings announcement occurs during a non-business day, in order to maintain an event window ending 1 trading day after the earnings announcement date, it is converted to the first available business day preceding that date.

To ensure the absence of earnings announcements during the estimation window, I drop all the *postret* intervals occurring over the course of two years following the event window of an examined observation[3].

Finally, I windsorize the 1% tails of the buy-and-hold abnormal returns in each firm age group to account for the outlier problems in the data.

4.1.2 Hypothesis Testing – H1

Having created all the variables I insert them into regressions in order to test my predictions. I start with estimating a regression capturing the sensitivity of abnormal returns to earnings surprises over the course of firm's aging. This regression takes the following form:

$$\begin{aligned} BHAR_{i,t} = \alpha + \beta_1 * AGE_{i,t} + \beta_2 * SURPRISE_{i,t} \\ + \beta_3 * (SURPRISE_{i,t} * AGE_{i,t}) + \epsilon_{i,t} \end{aligned} \tag{4.6}$$

where

$BHAR_{i,t}$ = the buy-and-hold abnormal return for company i related to the quarterly earnings announcements in quarter t;

$AGE_{i,t}$ = reciprocal of 2 plus the age of firm i in quarter t;

$SURPRISE_{i,t}$ = variable taking the value of 1 if a surprise is positive; 0 if there is no surprise; -1 if a surprise is negative.

The scope of this test is to validate the H1 and thereby provide a solid ground for testing further predictions. The intercept measures the expected abnormal return during the *postret* interval in case of no earnings surprise for firms whose age triggers low values of the AGE variable – hence for the oldest firms. The coefficient on AGE,

[3] In order to avoid an excessive reduction of trading days within the estimation period, subsequent *postret* intervals start on the forecast period end date instead of 12 days before this date.

divided by the sum of two and the firm age, provides an estimate of the expected abnormal return differential during the *postret* interval between the adjacent firm age values in case of no earnings surprise. The coefficient on $SURPRISE$ captures the correlation of earnings surprises and stock returns. If stock returns depend on the sign of earnings surprises, we should observe a positive and significant coefficient on $SURPRISE$. Finally, the coefficient on the interaction term $SURPRISE*AGE$ reflects the differential responsiveness to earnings surprises as a function of firm age.

If indeed investors learn about the stocks' true profitability during the subsequent earnings announcements (instead of naïvely overreacting to the adverse surprises), I expect to find a positive and significant coefficient on $SURPRISE * AGE$.

4.1.3 Hypothesis Testing – H2

The second regression tests the H2 by allowing for the asymmetric response to positive and negative earnings news as a function of the company age. This regression formula is as follows:

$$\begin{aligned} BHAR_{i,t} = \alpha + \beta_1 * AGE_{i,t} + \beta_2 * GOOD_{i,t} + \beta_3 * BAD_{i,t} \\ + \beta_4 * (GOOD_{i,t} * AGE_{i,t}) + \beta_5 * (BAD_{i,t} * AGE_{i,t}) + \epsilon_{i,t} \end{aligned} \tag{4.7}$$

where

$BHAR_{i,t}$ = the buy-and-hold abnormal return for company i related to the quarterly earnings announcements in quarter t;

$AGE_{i,t}$ = reciprocal of 2 plus the age of firm i in quarter t;

$GOOD_{i,t}$ = variable taking the value of 1 if a surprise in quarter t is positive;

$BAD_{i,t}$ = variable taking the value of 1 if a surprise in quarter t is negative.

In this model, the intercept provides an estimate of the expected abnormal return during the *postret* interval for the oldest firms in case of no earnings surprise. The coefficient on AGE measures the expected abnormal return differential during the *postret* interval on the zero earnings surprise observations in the adjacent firm age categories. The coefficient on the $GOOD$ (BAD) dummy variable accounts for the incremental return during the *postret* interval for the oldest companies associated with positive (negative) earnings surprises. Finally, the coefficient on the interaction term $GOOD * AGE$ ($BAD * AGE$) estimates the return differential for positive (negative) earnings surprises between the adjacent firm age categories.

If the negative earnings surprises indeed exert stronger impact on the stock prices than the positive news do when investors are faced with more uncertainty, I expect the coefficient on $BAD * AGE$ to be statistically significant and to have a higher magnitude than the coefficient on $GOOD * AGE$.

4.1.4 Hypothesis Testing – H3

In order to test the H3, I divide the sampled firms into 5 (quintile) *SIZE* portfolios based on the value of their total assets. To be more precise, for each fiscal quarter of every company I calculate the natural logarithm of book value of its total assets. On the basis of these values, for every calendar quarter of the examined period, I generate quintile portfolios. Afterwards I subject each of the quintile portfolios to the second regression (4.6).

This is the ultimate test to provide a robust evidence that the higher stock prices responsiveness to the negative earnings surprises among growth/young companies (and thereby $AMOUES$) can be indeed attributed to a higher level of uncertainty that investors face. Therefore, I expect to find the strongest asymmetry in the magnitudes of the interaction terms $GOOD * AGE$ and $BAD * AGE$ in the subsample of the smallest companies and a weaker differential effect in the portfolio of the largest firms.

4.1.5 Robustness of the Estimations

Regressions listed in the previous subsections make various intrinsic assumptions about the relationship between independent and dependent variables. But probably, most important and relevant assumption will be on error term $\epsilon_{i,t}$.

In case of *generalized linear models* (henceforth GLM), I expect following to be true regarding the error term:

- ◇ Error terms $\epsilon_{i,t}$ are independent, identically distributed (i.i.d.) for different t;
- ◇ Error terms follow a normal distribution $\mathcal{N}(0, \sigma^2)$ with 0 mean σ variance.

Tests for normality of error term can be carried out using statistical tests for normality such as performing a t-test on $\mathbf{E}(\epsilon_{i,t})$ where $H_0 : \epsilon_{i,t} = 0$ should not be rejected (thus a small t-statistic be expected) to check if the resulting error term from a regression is indeed normally distributed. If the assumption does not hold, Gauss-Markov theorem still states that as long as errors are uncorrelated with 0 mean and constant variance σ, *best linear unbiased estimator* (henceforth *BLUE*) will be the *GLM* model. Thus, as long as 0 mean and independent distribution holds, *GLM* regression models prove to be the *BLUE* estimator.

β_i coefficients coming from the regressions will have a certain p-value attached to them, as well as their magnitude. I will check p-values to test for significance of that particular coefficient in response to the dependent variable, which will quantize the effect of the accompanying independent variable on the dependent variable. For instance, if β_i has a p-value of 0.021, we can say that the independent variable x_i has a significance of 0.05 since $p < 0.05$.

However, this does not answer my question about the magnitude difference between the coefficients. One should check if the difference in magnitude is statistically significant. For this, I utilize the Wald Test as follows:

- ◇ If both β_i and β_j have the same sign, to check the magnitude difference, one needs to test the hypothesis $H_0 : \beta_i - \beta_j = 0$ to prove if the corresponding x_i and x_j indeed have different degrees of effect on the dependent variable;

- ◇ If β_i and β_j have opposite signs, to verify the asymmetrical response between these two coefficients, one needs to test the hypothesis $H_0 : \beta_i + \beta_j = 0$ to show if x_i and x_j exhibit the different magnitude of effect on the dependent variable.

In order to test these hypotheses by using the Wald Test, I calculate the associated t-statistic as:

$$t = \frac{\beta_i \pm \beta_j}{Var(\beta_i \pm \beta_j)} = \frac{\beta_i \pm \beta_j}{Var(\beta_i) + Var(\beta_j) \pm 2 * Cov(\beta_i, \beta_j)} \tag{4.8}$$

where

$Var(\beta_{i,j}) = (stdev(\beta_{i,j}))^2$;

$Cov(\beta_i, \beta_j)$ = covariance between the two coefficients, that can be gathered from the *variance-covariance matrix* of the corresponding regression.

Using this t-statistic and $Degrees\ of\ Freedom = \#Regressors - 1$, I estimate the associated p-value from a two-tailed t-distribution.

Another important assumption of *GLM* models is that the error is homogeneously distributed across the range of values of the dependent variable. Opposite would mean I have the heteroscedastic data which would deem the t-statistics on coefficients irrelevant, posing a problem for the *GLM* model.

To test for heteroscedasticity I need to look if the error term $\epsilon_{i,t}$ is uniformly distributed across the range of values of the dependent variable for all the regressions in the H1, H2 & H3. Therefore, I provide the reader with a series of scatter plots of $\epsilon_{i,t}$ vs. the predicted variable to demonstrate the distribution of the error across the range of the latter. To address any possible risk of heteroscedasticity in my regressions, I use the Huber-White technique to get more robust standard errors.

4.2 Methodology for BSI Analysis

4.2.1 Construction of BSI Ratio

Second part of my analysis concentrates on the behavior of different investor groups in response to quarterly earnings surprises. Specifically, I compare behavioral patterns among individual and institutional investors regarding positive and negative earnings surprises of companies belonging to different age classes by looking at stock purchases and sales during the *postret* interval[4]. Thereby, I divide the quarterly observations into the following firm age portfolios: [$<$ 1 year old], [1 year old], [2 years old], [3 years old], [4 years old], [5 years old], [6–10 years old], [11–15 years old], [16–20 years old], and [$>$ 20 years old][5]. This gives me 20 age-surprise based portfolios for each investor category:

- ▷ 10 portfolios for the trades related to the *positive* earnings surprises;
- ▷ 10 portfolios for the trades related to the *negative* earnings surprises.

[4] In case trade date occurs during a non-business day, it is converted to the first available business day following that date since the trades can be executed only during business dates.

[5] For example, the portfolio [$<$ 1 year old] encompasses all the sampled stocks that are aged less than 1 year during the forecast period end.

In order to create a unique measure that will facilitate the comparison of behavioral patterns between different investor categories, I follow and expand the method of Barber and Odean (2008): for every portfolio I calculate *the buy-sell imbalances* as follows:

$$BSI_p = \frac{1}{N_p N_t} \frac{\sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} NB_{i,t} - \sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} NS_{i,t}}{\sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} NB_{i,t} + \sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} NS_{i,t}} \tag{4.9}$$

where

BSI_p = the buy-sell imbalance of portfolio p;

$NB_{i,t}$ = number of purchases of stock for firm i in portfolio p over quarter t;

$NS_{i,t}$ = number of sales of stock for firm i in portfolio p over quarter t;

N_t, N_p = number of quarters in observation dataset, number of firms in portfolio p.

Additionally, I create my own buy-sell imbalances ratio – *"VBSI"*, which is based on the imbalances in the volume of shares purchased and the volume of shares sold for a particular company during the examined interval. My motivation for this undertaking is the conviction that the total number of purchases/sales of a given stock is less informative than the total purchased/sold volume of the same stock, as the trades diverge in the quantity[6]. The volume buy-sell imbalances formula takes the following form:

$$VBSI_p = \frac{1}{N_p N_t} \frac{\sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} |VB_{i,t}| - \sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} |VS_{i,t}|}{\sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} |VB_{i,t}| + \sum\limits_{t=1}^{n_t} \sum\limits_{i=1}^{n_p} |VS_{i,t}|} \tag{4.10}$$

where

$VBSI_p$ = the trade volume based buy-sell imbalance of portfolio p;

[6]For instance, given 10 acquisitions of 50 shares each and 5 disposals of 200 shares each during the *postret* interval of firm i in quarter t, the original *BSI* ratio indicates positive buy-sell imbalance, whereas the true imbalance is negative.

$VB_{i,t}$ = total purchased volume of stock for firm i in portfolio p over quarter t;

$VS_{i,t}$ = total sold volume of stock for firm i in portfolio p over quarter t;

N_t, N_p = number of quarters in observation dataset, number of firms in portfolio p.

4.2.2 Hypothesis Testing – H4

Thereafter, to test the H4 I compare the differences in *(V)BSI* between individual and institutional portfolios for the same type of surprise in the same firm-age groups.

Since institutional investors are believed to revise their expectations about stocks' profitability due to learning from the earnings surprises, I expect to find higher values of *(V)BSI* in case of positive surprises and lower values of *(V)BSI* in case of negative news. In other words, institutional investors are expected to buy to a larger extent (to sell to a lesser extent) stocks related to positive earnings surprises than those associated with negative earnings surprises. Furthermore, *(V)BSI* linked to positive news should have positive sign (investors are expected to undertake more acquisitions than sales), whereas *(V)BSI* related to negative news should have negative sign (investors are expected to undertake more sales than acquisitions).

As already mentioned, in case of individual investors, financial literature presents ambiguous evidence about their trading behavior following earnings surprises. Some of the results suggest that individuals tend to be net buyers irrespective of the sign of a surprise (e.g. Barber and Odean, 2008; Hirshleifer et al.,2008). Others imply that individual investors display the contrarian-to-momentum behavior (e.g. Bartov et al., 2000; Kaniel et al., 2012). Thus, although it is difficult to predict the individual investors' behavior related to positive surprises, the evidence regarding their trading patterns associated with negative news leads to more conclusive expectations. Since individuals demonstrate to be net buyers after negative surprises, I expect their *(V)BSI* linked to the negative earnings news to have a positive sign. In other words, in this situation individuals are expected to display a surplus of purchases over sales. Additionally, assuming that individuals are indeed contrarian investors inclined to the disposition effect, I expect them to sell to a larger extent (to purchase to a lesser extent) stocks related to positive earnings surprises than those associated with negative earnings surprises.

The next implication of resolving uncertainty in finance is that its pace declines with firm's aging. Therefore, I expect the differential between *(V)BSI* related to positive news and *(V)BSI* related to negative news (henceforth Δ*(V)BSI*) to decrease with company's aging, as the level of uncertainty becomes gradually lower, and hence triggers less overreaction to the earnings announcements. I expect to find such a pattern primarily within the portfolios of institutional investors, as this investor group is believed to learn about firms' profitability at a faster pace than individuals.

4.2.3 Hypothesis Testing – H5

Finally, to test the H5 I examine the differences in the buy-sell imbalances displayed by individual investors over the course of their trading experience.

Following Seru et al. (2010), I use cumulative number of trades an investor has placed as a measure of trading experience. The results of the aforementioned study indicate that investors primarily learn by trading, and hence this measure performs significantly better than the analysis using years of trading as a proxy for trading experience. Therefore, I divide the individual trades into three groups based on the cumulative number of trades assigned to an account performing such a trade: [1–50 trades], [51–100 trades], and [>100 trades][7]. Finally, I divide each of these groups into 20 age-surprise categories, according to the procedure described earlier. This provides me with 60 age-surprise based portfolios.

Since more experienced investors are believed to be more prone to learn about stocks' profitability during earnings announcements, I expect to find positive values of Δ*(V)BSI* within this investor group, especially for young companies. Specifically, more experienced individuals are expected to acquire to a larger extent (to sell to a lesser extent) stocks linked to positive earnings surprises than those associated with negative earnings surprises. The reverse should hold for the investment behavior of this investor group connected to negative earnings surprises. I expect *(V)BSI*'s related to positive surprises to have a positive sign, whereas *(V)BSI*'s associated with negative surprises to have a negative sign.

[7]Where [1–50 trades] accounts for the smallest experience and [>100 trades] denotes the largest experience.

4.2.4 Robustness of the Estimations

Regarding testing the robustness of my claims for the H4 and H5, I test the statistical significance of differences of *(V)BSI*. Since my final *(V)BSI* values are defined as the mean of *(V)BSI*'s of stocks which can be regarded as random variables drawn from a randomized distribution, I utilize a two-sample t-statistic to test $H_0 : \mu_1 = \mu_2$ against $H_a : \mu_1 \neq \mu_2$ i.e. $H_0 : \mu_1 - \mu_2 = 0$ against $H_a : \mu_1 - \mu_2 \neq 0$. Thus, using my two-sample t-statistic, defined as:

$$t = \frac{(\overline{x_1} - \overline{x_2}) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4.11}$$

where

$\overline{x_1}$, $\overline{x_2}$ = sample means;

s_1 , s_2 = sample standard deviations,

I calculate the associated two-tailed p-value with $n_1 + n_2 - 1$ degrees of freedom. I use two-tailed tests since difference can be significantly different from 0 in either direction (+/-) and I use the resulting p-value to test the robustness of my claims for the H4 and H5.

4.3 Contributions over Existing Research

My thesis provides new insights and several contributions over the established research to understand the cause of asymmetrical response to negative earnings surprises, an active topic within the financial research community.

Extending the work done by Skinner and Sloan (2002), I construct and utilize the *AGE* variable in regressions 4.6 and 4.7 as a proxy for uncertainty about stock profitability. This step enables me to expand the scope of the research on asymmetrical response to earnings surprises beyond the investor naivety explanation by providing ample support that uncertainty about a particular stock is the primary driver of this behavior.

Using and extending the *buy-sell imbalances* method by Barber and Odean (2008), I apply it to examine the trading patterns of institutional and individual investors within the *postret* period around the earnings announcements. The construction of portfolios based on the company age enables me to capture the existence of learning about stock profitability. So far, learning ability of a particular investor group around earnings announcements has not been examined within financial literature. I do not only look at the imbalances in the number of trades, but also I examine the imbalances in the total traded volume of a particular stock. The *buy-sell imbalances* method helps me further to resolve the dilemma whether the higher responsiveness to the negative surprises stems from the naivety of investors or from the uncertainty about stock profitability.

Chapter 5

Data Selection

In this chapter I describe in detail the data sources and the collection methodologies that I have followed while gathering the datasets that are to be utilized in the statistical tests. In order to provide valid, representative data for testing my hypotheses, the analysis should not be limited to only a singular dataset, but instead encompass datasets from various resources.

5.1 Earnings Surprise Data

Sample selection starts with gathering data regarding earnings announcements and their corresponding forecasts. I use quarterly historical records from the Institutional Brokers' Estimate System (henceforth I/B/E/S), which provides me with 3 109 588 observations containing earnings announcement dates, forecasts of *EPS* and realized *EPS* for the period 1991-2010.

For each earnings-announcement observation, I select the last available consensus median forecast generated before the end of forecast period which makes it a robust and reliable measure since such a prognosis accounts for recent changes in the evaluations, while still being deprived of any information from earnings pre-announcements. This operation reduces my sample to 321 292 firm-quarter observations.

If forecast *EPS* are lower (higher) than realized *EPS*, I treat such an observation as a positive (negative) earnings surprise. If forecast *EPS* are exactly the same as realized *EPS*, I label such an observation as "zero", which indicates no earnings surprise. Moreover, I control for multiple forecast periods within the same calendar quarter related to a single CUSIP number and I select the latest one for my analysis (apparently a company had changed fiscal year specifications during such a calendar quarter). Finally, I eliminate the observations where earnings announcements occur later than within 3 months following the forecast period end. Due to these adjustments, my final I/B/E/S sample is reduced to 318 153 observations.

5.2 Expected Return Data

In order to examine responses to earnings surprises, my analysis requires the daily common stock return data adjusted for dividend payments, which I obtain from the Center for Research in Security Prices (henceforth CRSP). Moreover, CRSP also enables me to estimate R_m according to the procedure described earlier since it provides information on the total number of shares outstanding and their price on a daily basis. Overall, CRSP dataset contains stock market data of 467 748 firm-quarters for the period 1991-2010. However, only 220 332 of them are overlapping with the I/B/E/S firm-quarters for the same period.

As a proxy for R_f I use the 3-month Treasury Bill rate (adequate for the calculation date), which is available in form of time-series data on the Federal Bank of St. Louis website.

5.3 Firm's Characteristics Data

Subsequently, I extract the data related to financial and market characteristics of the examined companies from COMPUSTAT quarterly database. The raw dataset comprises 912 216 firm-quarter observations for the period 31.12.1990–31.12.2010. I deliberately include the data reported at the end of year 1990 since it is relevant for earnings announcements taking place during the first quarter of 1991.

Over the course of formatting COMPUSTAT dataset, I eliminate multiple observations on a single CUSIP related to the same calendar quarter or/and to the same fiscal quarter (this decreases my sample to 909 454 observations). In case of missing quarterly accounting data of a company in at most 3 quarters of one fiscal year, I complete it by referring for simplicity to the available information disclosed at the end of the relevant fiscal year or to the mean of the half-year disclosures[1]. Finally, while merging COMPUSTAT with I/B/E/S and CRSP, the number of observations in my sample falls to 201 919.

In order to avoid contamination of the dataset with the stock price reactions to other influential events, I exclude quarters containing information of the mergers and acquisitions (M&A) activity and the common stock repurchases. I also drop the observations that do not satisfy the required number of days in the estimation period. These operations further reduce my sample to 157 024 observations.

Following Pástor and Veronesi (2003), I estimate the age of firms by looking at the IPO date information in COMPUSTAT and by controlling for the first stock price record in CRSP. I select the earlier of these two figures as the inception date of the firm's activity. The counting starts with the value of 0 for the year of firm's inception and increases by 1 on each subsequent "birthday" date. Due to a scarce number of observations for the oldest firms, I restrict the maximal firm age for my sample to 60. The grand median of the firm age is 14. After this adjustment, my sample contains 148 111 observations.

Finally, I obtain from COMPUSTAT the quarterly book values of firms' total assets which allows me to generate 5 (quintile) *SIZE* portfolios. Since such information is not available for all the sampled firm-quarters, in test of the H3 my sample decreases to 147 661 observations.

5.4 Investor Trading Data

Second part of the analysis revolves around behavior of different investor groups in response to the quarterly earnings announcements. The primary dataset used in this part of the research are records from a large discount brokerage firm operating in the US. Data contains trades of 48 226 households performed in the period from January 1991 to December 1996 and enables an investigation on the trading behavior of both individual and institutional investors. I acknowledge that the institutional clients of this large discount brokerage firm are mostly small companies, representative only for the small enterprises sector. I classify an investor as "individual"

[1]For some of the early observations of COMPUSTAT, the data was disclosed once (at the end of a fiscal year) or twice (every half-year) instead of 4 times (at the end of each fiscal quarter).

if their account is registered as *INDIVIDUAL*. Alternatively, I label a household as "institutional investor" if their account is registered as *CORPORATE*. In order to avoid contamination of the dataset with non-coherent patterns in the singular investor trading behavior, I control for multiple account opening dates associated with a single account number. In case of duplicates, I preserve the observations belonging to the account opened most recently. Moreover, in the analysis I only concentrate on purchases and sales regarding securities labeled as common stock. In all, the sample period contains 138 057 trades performed by 24 081 individuals and 2 474 trades performed by 329 institutions.

The construction of the cumulative number of trades requires sampled households to have an account opened no earlier than in 1991, in order to account for all the trades placed by an investor since the beginning of their trading experience[2]. In my study, counting the cumulative number of trades starts with 1 on the earliest trade date associated with an account and increases by 1 with every subsequent trade, irrespective of the type of a traded security. This condition reduces the sample to 18 211 trades of 3 881 individuals.

Since the number of trades of institutional clients of the large discount brokerage firm is significantly smaller than the number of transactions of individual clients, and the former type of traders is only representative for small enterprises, I further analyze trading patterns of institutional investors by the means of an additional dataset. I obtain the information on quarterly changes in institutional common stock holdings reported in the Securities and Exchange Commission's (SEC) Form 13F from Thomson Reuters. This database classifies the institutional investors into the following groups: *BANKS*, *INSURANCE COMPANIES*, *INVESTMENT COMPANIES & THEIR MANAGERS*, *INVESTMENT ADVISORS*, and *ALL OTHERS* (*pension funds*, *university endowments*, *foundations*). In order to ensure the coherence of both datasets, I examine only the data regarding the period between 1991 and 1996.

When comparing behavioral patterns of large institutional investors related to positive and negative earnings surprises, my capabilities of conducting a thorough analysis become limited. As Thomson Reuters enables me to examine only the net

[2] As the dataset contains only the transactions made during the years 1991-1996, this variable is only relevant in case of accounts opened since 1991.

change of particular common stocks held by institutions at the end of a calendar quarter, I cannot analyze the patterns in stock purchases and sales during the exact *postret* interval. Therefore, the buy-sell imbalances are prone to be contaminated by other influential events and should be treated rather as an approximation of general patterns. Another limitation of this analysis is the lack of information about the total number of purchases and sales of a particular stock, and hence the inability to calculate the original *BSI*. In this regard I calculate the buy-sell imbalances using only the *VBSI* ratio.

While formatting the Thomson Reuters dataset, I first control for multiple earnings announcements occurring in the same calendar quarter associated with a single company[3]. In case of duplicates, I preserve only the observation belonging to the latest earnings announcement (as 13F Filings are submitted at the end of a calendar quarter, in this case the latest earnings announcement is expected to exert the highest impact on the institutional holdings). Thereafter, I calculate the *VBSI* for a particular firm-quarter observation by looking at the respective total negative and total positive volume changes reported at the end of the same quarter when *EPS* was released. In total, the sample contains 3 674 462 changes in holdings reported by 1 738 managers following 55 551 earnings announcements.

[3]Sometimes *EPS* happen to be announced before the end of forecast period end. Thus, within one calendar quarter there may occur two announcements released by the same company: one related to the previous quarter, the other one related to the current quarter.

Chapter 6

Results and Analysis

In this chapter I present empirical verification of my hypotheses. I begin by providing a descriptive evidence on the predicted relation between the company age and the stock returns responsiveness to different signs of quarterly earnings surprises. Thereafter, I conduct statistical tests for each of my predictions. I start by regressing abnormal buy-and-hold returns on various sets of variables in order to investigate the first three hypotheses. Subsequently, I perform an analysis of differences in *BSI* ratios for various groups of investors, conditional on the firm age.

6.1 Descriptive Evidence

Table 6.1 reports the mean buy-and-hold abnormal returns related to earnings announcements as a descriptive evidence on the relation between the firm age and the stock returns responsiveness to different signs (positive; zero – i.e. no surprise; negative) of quarterly earnings surprises. All the firm-quarter observations are assigned to 10 *Firm Age* categories based on the company age on the forecast period end date. Additionally, each *Firm Age* category is further divided into 3 subportfolios based on the sign of a quarterly earnings surprise. For each of the resulting 30 subportfolios, Table 6.1 reports the quarterly mean buy-and-hold abnormal return calculated during the *postret* interval, the number of observations and the proportion of each *Firm Age* category's observations falling into that subportfolio. The column at the far right provides the grand averages for all the *Firm Age* portfolios.

Table 6.1: Mean Buy-and-Hold Abnormal Returns related to Earnings Announcements

Earnings Surprise portfolios are created based on the sign (positive; zero; negative) of quarterly earnings surprises for the period 1991-2010. *Firm Age* portfolios are created based on the company age on the forecast period end date (counting of age starts with the value of 0 on the IPO date).

	Earnings Surprise Portfolio			
	Positive	Zero	Negative	All
Firm Age Portfolio				
	3.15%	-1.57%	-7.63%	-0.65%
< 1 year old	1371	297	706	2374
	(57.8%)	(12.5%)	(29.7%)	(100.0%)
	2.60%	-2.52%	-8.22%	-1.71%
1 years old	5139	1289	3241	9669
	(53.1%)	(13.3%)	(33.5%)	(100.0%)
	3.62%	-1.47%	-7.18%	-1.03%
2 years old	4743	1189	3501	9433
	(50.3%)	(12.6%)	(37.1%)	(100.0%)
	3.31%	-0.51%	-6.68%	-0.77%
3 years old	4382	1097	3072	8551
	(51.2%)	(12.8%)	(35.9%)	(100.0%)
	3.80%	-2.39%	-6.50%	-0.80%
4 years old	3847	917	2861	7625
	(50.5%)	(12.0%)	(37.5%)	(100.0%)
	3.69%	-0.31%	-5.91%	-0.36%
5 years old	3616	816	2641	7073
	(51.1%)	(11.5%)	(37.3%)	(100.0%)
	3.42%	-1.33%	-5.36%	-0.40%
6–10 years old	15626	3321	11399	30346
	(51.5%)	(10.9%)	(37.6%)	(100.0%)
	3.51%	-1.00%	-4.63%	0.07%
11–20 years old	18468	3570	12705	34743
	(53.2%)	(10.3%)	(36.6%)	(100.0%)
	2.59%	-0.84%	-3.67%	-0.15%
21–40 years old	16798	3522	12382	32702
	(52.6%)	(10.3%)	(37.1%)	(100.0%)
	2.22%	-0.26%	-2.74%	0.29%
41–60 years old	3184	460	1951	5595
	(52.2%)	(11.1%)	(36.7%)	(100.0%)

While looking at the rightmost column, we can observe an almost monotonic increase in the average abnormal return throughout the firm's aging (from –1.71% for 1-year-old firms to 0.29% for the portfolio of the oldest companies). This translates into a 2% differential and tells us that during the *postret* interval, younger companies overall perform worse than their older counterparts. This finding is consistent with the financial evidence about value stocks outperforming growth (glamour) stocks.

Columns 2 and 4 of Table 6.1 provide a descriptive evidence in favor of H2 and partially for H1. First of all, we observe that the absolute value of stock returns around earnings announcements is lowest in the portfolio of the oldest companies, both for positive and negative surprises (2.22% and –2.74%, respectively). Therefore, it can be argued that the influence of earnings surprises on stock prices decreases with time. However, abnormal returns related to positive surprises in general oscillate around 3.5% without displaying any clear trend (especially for the first eight firm–age portfolios). On the other hand, abnormal returns related to negative surprises demonstrate a strong downward slopping trend: their absolute magnitude declines monotonically as firm age increases (ranging from –8.22% for 1-year-old companies to –2.74% for the portfolio of the oldest firms). Moreover, in every $Firm\,Age$ portfolio, the absolute value of mean abnormal return related to negative surprises is always higher than the absolute value of that related to positive surprises (e.g. –7.18% vs 3.62% respectively for 2-year-old firms, whereas –5.91% vs 3.69% respectively for 5-year-old firms). This trend suggests that stocks are characterized by higher responsiveness to negative earnings surprises than to positive surprises. More importantly, the impact of negative news on stock price appears to be highest for the youngest companies and to sharply attenuate across the subsequent $Firm\,Age$ portfolios.

The observed pattern is consistent with the financial evidence that investors are excessively optimistic about profitability of growth (young) stocks, as when faced with bad news, they punish more severely growth (young) stocks than value (old) stocks. On the other hand, this trend is also coherent with the dynamics of resolving uncertainty documented in the past financial research (e.g. Pástor and Veronesi, 2003): the pace of resolving uncertainty declines over the course of company's aging. As investors learn about the stock's true profitability, at the time of each consecutive earnings announcements they are less disappointed. Finally, the pattern observed in the column 4 of Table 6.1 coincides with the trend in the rightmost column: it can be

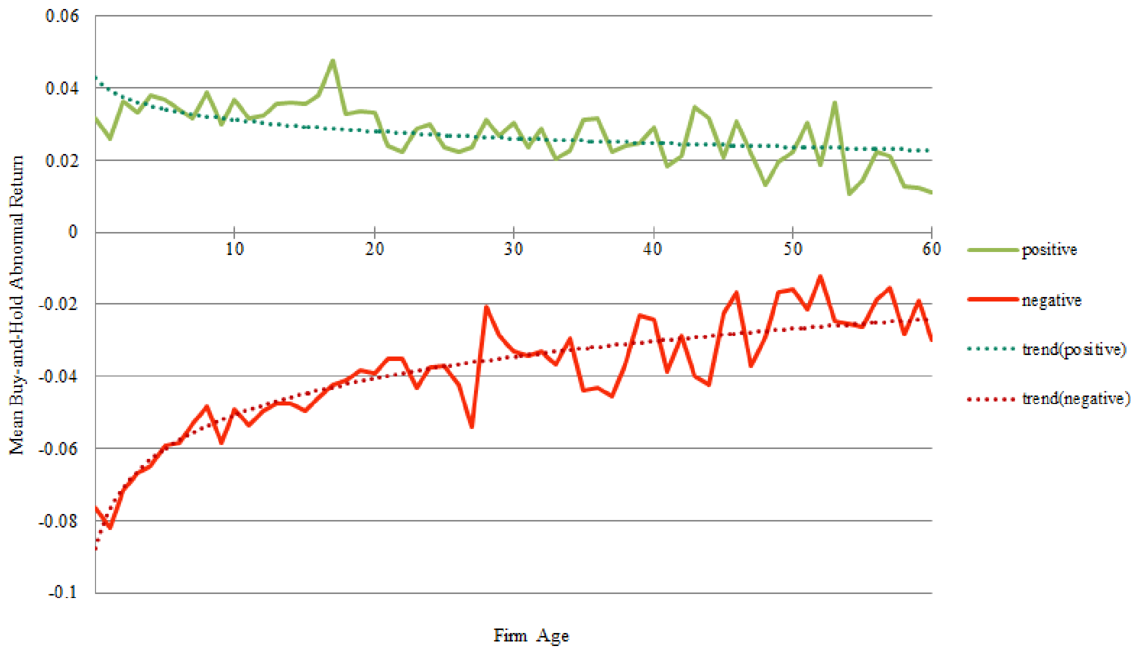

Figure 6.1: Mean Buy-and-Hold Abnormal Returns related to Earnings Announcements by the Sign of an Earnings Surprise
The graph plots the mean abnormal buy-and-hold return by the sign of an earnings surprise against each subsequent firm age group. *Earnings Surprise* portfolios are created based on the sign (positive or negative) of quarterly earnings surprises for the period 1991-2010. On the *Firm Age* axis, each value accounts for the company age on the forecast period end date (counting of age starts with the value of 0 on the IPO date). Additionally, the graph plots the logarithmic trends for both *Earnings Surprise* portfolios (dotted lines).

inferred that the return differential between growth/young and value/old companies arises due to the asymmetric response to negative earnings news.

To illustrate in detail stock return patterns around earnings announcements, Figure 6.1 plots the mean abnormal buy-and-hold returns for positive and negative earnings surprises against each subsequent firm age group. Additionally, it also plots the logarithmic trends for both surprise signs. The graph clearly demonstrates that the impact of earnings surprises on stock returns declines throughout company's aging. Irrespectively of the sign of a surprise, all the abnormal returns approach 0 as we move over the successive firm age groups. Furthermore, the decline in the mean abnormal return within the negative surprise portfolio is clearly steeper than that within the positive surprise portfolio.

Overall, Table 6.1 and Figure 6.1 provide a preliminary evidence in support of my first two hypotheses. In the following sections I will further test my predictions by the means of a statistical analysis.

6.2 Regression Analysis

In this section I statistically test my first three hypotheses by conducting a regression analysis. Firstly, I regress abnormal buy-and-hold stock returns on the AGE variable, on the sign of an earnings surprise and on the interaction term between AGE & *the surprise sign*, as in the equation 4.6. Subsequently, I test my main prediction, presented in the H2, by regressing abnormal buy-and-hold stock returns on the AGE variable, on the dummy variable for the sign of an earnings surprise and on the interaction term between AGE & *the dummy variable*, as in the equation 4.7. Finally, I test the H3 by subjecting each of the quintile $SIZE$ portfolios to the equation 4.7.

Table 6.2 presents the estimated regression coefficients with their t-statistics in parentheses. The second leftmost column reports the coefficients of the first regression. The coefficient on AGE is negative and statistically significant (–0.062; t=–13.32). In line with the results of previous financial research, we find a positive and statistically highly significant coefficient on $SURPRISE$ (0.034; t=57.06), which confirms that there is a correlation between stock returns and the sign of earnings surprises. Finally, consistent with my predictions, we observe that the coefficient on $SURPRISE * AGE$ is positive and statistically highly significant (0.071; t=14.27), which suggests that earnings surprises have higher impact on stock returns of younger firms than on those of their older counterparts. Moreover, since the construction of the AGE variable accounts for the pace of resolution of uncertainty[1], we observe a steeper decline in the resolution of uncertainty for younger firms and a milder decline for older companies. Given all this, investors appear to indeed learn about firm's true profitability during subsequent earnings announcements, which affects the magnitude of impact of earnings surprises on stock returns.

If the effect of earnings surprises on the differential returns between young and old stocks was not distinguishable from the general investor sentiments about these two groups of stocks, then one would observe that the coefficients on $SURPRISE*AGE$

[1]most rapid at the beginning of learning and slowing down over time

Table 6.2: Estimated Coefficients from Regression of Abnormal Stock Returns on Variables related to Learning about Stock Profitability

Estimated coefficients (with t-statistics in parentheses) from regressions of buy-and-hold abnormal returns ($BHAR$) related to the quarterly earnings announcements on the subsets of following variables: AGE (the reciprocal of two plus firm age), $SURPRISE$ (a variable that takes the value of 1 if an earnings surprise is positive; 0 if there is no surprise; –1 if a surprise is negative), $GOOD$ (a dummy variable for positive earnings surprises), and BAD (a dummy variable for negative earnings surprises). The first regression tests the H1, the next one tests the H2, and the last five regressions test the H3 (controlling for the quarterly book value of firm's assets, the observations are assigned to five portfolios, based on the natural log of total assets, where 1 denotes the smallest-firm-quintile and 5 denotes the largest-firm-quintile). The last two rows indicate R^2 and the number of observations.

	H1	H2	H3 – $SIZE$				
			1	2	3	4	5
$Intercept$	-0.003^{***}	-0.007^{***}	-0.016^{***}	-0.012^{***}	-0.006	-0.007^{**}	-0.006^{**}
	(-5.67)	(-4.80)	(-3.16)	(-2.62)	(-1.63)	(-2.45)	(-2.57)
AGE	-0.062^{***}	-0.035^{***}	-0.004	-0.056^{*}	-0.042	0.012	0.004
	(-13.32)	(-2.93)	(-0.14)	(-1.95)	(-1.55)	(0.45)	(0.17)
$SURPRISE$	0.034^{***}						
	(57.06)						
$SURPRISE \times AGE$	0.071^{***}						
	(14.27)						
$GOOD$		0.039^{***}	0.055^{***}	0.057^{***}	0.038^{***}	0.035^{***}	0.026^{***}
		(22.46)	(9.85)	(11.68)	(9.90)	(10.79)	(10.39)
BAD		-0.029^{***}	-0.039^{***}	-0.036^{***}	-0.038^{***}	-0.030^{***}	-0.019^{***}
		(-16.02)	(-6.92)	(-7.16)	(-9.37)	(-8.67)	(-7.29)
$GOOD \times AGE$		0.042^{***}	-0.030	0.016	0.054^{*}	0.010	0.026
		(3.10)	(-1.02)	(0.51)	(1.77)	(0.35)	(0.97)
$BAD \times AGE$		-0.102^{***}	-0.135^{***}	-0.061^{*}	-0.003	-0.035	-0.041
		(-7.05)	(-4.44)	(-1.82)	(-0.10)	(-1.11)	(-1.41)
R^2	7.16%	7.16%	7.60%	8.63%	7.37%	6.71%	4.99%
$Observations$	148 111	148 111	29 566	29 534	29 529	29 534	29 498

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

and on AGE are not statistically different from each other. On the other hand, if the overreaction arisen due to resolving uncertainty about stock profitability was not discernible from a simple reaction to the sign of a surprise, then we would see that the coefficients on $SURPRISE*AGE$ and on $SURPRISE$ are not statistically different from each other. To account for these two possibilities, I analyze the results of the Wald Test reported in Appendix A in Table A.1. In both cases, the estimated Wald statistics (t=17.71 and t=7.28, respectively) indicate that the coefficients are significantly different from one another. Thus, the test of the H1 provides a clear evidence that investors do learn about stocks' actual profitability at the time of earnings announcements. Such resolution of uncertainty results in different levels of responsiveness to the earnings surprises, conditional on the learning stage.

Overall, the first model indicates that, on average, the abnormal return of a 1-year-old company would oscillate around 3.40% in case of a positive surprise, and around –8.13% in case of a negative surprise, whereas for a 60-year-old company these values would be 3.11% and –3.91%, respectively[2].

The results from testing the H2 are presented in the column 3 of Table 6.2. The coefficient on AGE is negative and statistically significant. Moreover, we find highly statistically highly significant coefficients on the surprise dummies, and their signs are coherent with the expectations — good news appear to affect stock returns positively, whereas bad news appear to be detrimental for stock returns (0.039; t=22.46 for $GOOD$ vs. –0.029; t=–16.02 for BAD). If the investor reaction to the earnings announcements was not determined by their sign, then the coefficients on $GOOD$ and BAD should not be statistically different from each other. Results of the Wald Test reported in Table A.1 show that this is not the case. Not only investors do base their reaction on the sign of a surprise (t=56.71), but also they tend to overreact to positive surprises more strongly than to those negative (the difference in absolute values of both coefficients is significantly positive, with t=2.91). A larger magnitude of the coefficient on $GOOD$ is consistent with the belief underlying the research of Dreman and Berry (1995)[3]. Specifically, as these variables are particularly informative about

[2] $3.40\%=(-0.3\%)-6.2\%*\frac{1}{3}+3.4\%+7.1\%*\frac{1}{3}$
$-8.13\%=(-0.3\%)-6.2\%*\frac{1}{3}-3.4\%-7.1\%*\frac{1}{3}$
$3.11\%=(-0.3\%)-6.2\%*\frac{1}{62}+3.4\%+7.1\%*\frac{1}{62}$
$-3.91\%=(-0.3\%)-6.2\%*\frac{1}{62}-3.4\%-7.1\%*\frac{1}{62}$

[3] Precisely, earnings surprises characterized by the sign unexpected for a particular stock class should exert more influence on its stock returns than those attributed with the expected sign since

older firms[4] (which are expected to be less profitable), we observe that their stock returns appear indeed to be more influenced by positive earnings surprises than by those negative, in line with the "dual astonishment" effect. Finally, the coefficients on the interaction terms $GOOD * AGE$ and $BAD * AGE$ result to be statistically significant and to have the expected signs (0.042; t=3.10 & –0.102; t=–7.05, respectively). Additionally, the absolute value of the coefficient on $BAD*AGE$ is 2.4 times higher than that corresponding to $GOOD * AGE$. As demonstrated by the Wald Test reported in Table A.1, this asymmetry in the magnitudes of coefficients is statistically significant (t=–2.28). Consistent with the H2, the aforementioned results suggest that the impact of negative surprises on stock prices of young firms is significantly higher than the impact of positive news and this differential effect decreases over the course of firm's aging. The overreaction to negative news appears to weaken as investors resolve their uncertainty about the true stock profitability during the following earnings announcements.

As we move on to five rightmost columns of Table 6.2, we find results from the test of the H3. In four regressions we observe no statistically significant linear dependence of mean $BHAR$ on the AGE variable, and in one regression there is a weak statistical significance of the corresponding coefficient. In contrast, all of the coefficients on $GOOD$ and BAD are statistically highly significant and their signs are consistent with the expectations. Most importantly, the negative coefficient on $BAD * AGE$ is statistically significant only in two regressions conducted on the smallest stocks: regression with $SIZE = 1$ (–0.135; t=–4.44) and that with $SIZE = 2$ (–0.061; t=–1.82), and its magnitude is respectively 4.5 and 3.8 times higher that the one on $GOOD * AGE$. However, results of the Wald Test reported in Table A.1 reveal that the difference in the magnitudes of these two coefficients is statistically significant only in the regression with $SIZE = 1$ (t=–2.96). These results are consistent with the prediction: negative earnings surprises appear to exert higher impact on stock returns of younger firms, primarily among the smallest firms.

Overall, the reported findings indicate that investors' overreaction to earnings surprises (especially to those negative) is more pronounced when they are faced with

in such a case investors deal with the dual astonishment (regarding the surprise itself, as well as its sign).

[4] A high value of firm age in the denominator of the AGE variable remarkably decreases the expected values of AGE, $GOOD * AGE$, and $BAD * AGE$.

larger uncertainty. However, as they learn about the true stock profitability during the subsequent earnings announcements, the magnitude of their overreaction decreases. Given all that, it appears that higher uncertainty about firm's true profitability and a major reality check during the earnings announcements are the drivers of the higher responsiveness to the negative earnings surprises displayed by stock returns of young firms, which in turn causes $AMOUES$ and the return differential between growth and value stocks.

6.3 BSI Analysis

In this section I examine behavioral patterns of various investor types in order to identify which of them is more responsive to the earnings surprises of young stocks, especially to those negative. In this regard, I divide trades of every $Investor\,Category$ into portfolios based on the sign of an earnings surprise (positive or negative) and based on the age of a company whose stock is being traded. For each of these portfolios I calculate the mean *(V)BSI*. Finally, I calculate Δ*(V)BSI* for every $Firm\ Age$ portfolio within each $Investor\,Category$. The results are presented in Table 6.3.

Panel A of Table 6.3 reports the results for *BSI* ratios calculated via the number of trades. Within the category of individual investors, we observe that almost all *BSI* ratios associated with negative surprises have a positive sign and all of them are higher than those related to positive earnings news. On the other hand, the negative sign on a part of the *BSI*'s associated with positive surprises is in line with the disposition effect. These results demonstrate that individuals tend to buy (sell) stocks linked to negative earnings surprises to a larger (smaller) extent than those linked to positive earnings surprises, which is consistent with the contrarian trading behavior. For instance, the buy-sell imbalance is 9.80% if traded 1-year-old firms are associated with positive surprises, and 20.73% if such firms are associated with negative surprises. This means that, on average, out of all the shares of a 1-year-old company linked to a positive (negative) surprise and traded by individual investors, 9.80% (20.73%) of them constitutes a surplus of shares purchased over shares sold. Statistical significance of Δ*BSI* in the majority of $Firm\ Age$ portfolios indicates that the trading patterns for the opposite surprise signs are significantly different from each other. Overall, the findings are in line with the empirical prediction: individual

Table 6.3: Buy-Sell Imbalances related to Quarterly Earnings Announcements, by Investor Category

For every *Investor Category*, traded stocks are divided into subportfolios based on the sign (positive or negative) of an earnings surprise and based on the company age on the forecast period end date (counting of age starts with the value of 0 on the IPO date). Generated portfolios translate into 20 *(V)BSI* ratios for each investor category. For every *Firm Age* portfolio within the same *Investor Category* is calculated the difference between *(V)BSI* for positive surprises and *(V)BSI* for negative surprises (with t-statistics in parentheses). Panel A presents results for the original *BSI* ratio, whereas Panel B contains results for the *VBSI* (volume based buy-sell imbalances ratio).

Panel A - *BSI*

	Investor Category					
	Individuals			Small Enterprises		
	Positive	Negative	ΔBSI	Positive	Negative	ΔBSI
Firm Age Portfolio						
<1 year old	19.53%	31.53%	-12.00pp**	39.47%	21.57%	17.91pp
			(-2.36)			(0.57)
1 year old	9.80%	20.73%	-10.93pp***	9.80%	18.02%	-8.21pp
			(-3.28)			(-0.40)
2 years old	2.22%	14.93%	-12.72pp***	-22.01%	-8.55%	-13.47pp
			(-3.62)			(-0.67)
3 years old	-0.79%	7.94%	-8.73pp**	-27.03%	11.38%	-38.41pp*
			(-2.29)			(-1.84)
4 years old	-3.23%	3.15%	-6.38pp	-2.63%	3.51%	-6.14pp
			(-1.55)			(-0.25)
5 years old	0.68%	7.16%	-6.47pp	-2.15%	-8.75%	6.60pp
			(-1.52)			(0.30)
6–10 years old	-3.68%	5.52%	-9.21pp***	-5.62%	-1.28%	-4.34pp
			(-4.60)			(-0.43)
11–15 years old	-5.19%	-0.01%	-5.18pp*	-19.16%	-8.82%	-10.33pp
			(-1.70)			(-0.68)
16–20 years old	-6.00%	3.87%	-9.88pp***	-4.69%	15.87%	-20.56pp
			(-2.95)			(-1.21)
>20 years old	-12.72%	-4.38%	-8.34pp***	-11.28%	2.37%	-13.65pp**
			(-5.46)			(-1.97)

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

Panel B – *VBSI*

	Investor Category								
	Individuals			Small Enterprises			Large Institutional Investors (ALL)		
	Positive	Negative	$\Delta VBSI$	Positive	Negative	$\Delta VBSI$	Positive	Negative	$\Delta VBSI$
Firm Age Portfolio									
<1 year old	16.52%	28.46%	-11.94pp** (−2.23)	39.10%	18.95%	20.14pp (0.64)	24.33%	5.66%	18.66pp*** (9.23)
1 year old	6.66%	18.95%	-12.30pp*** (−3.53)	10.39%	12.93%	-2.54pp (−0.12)	17.32%	2.17%	15.15pp*** (11.39)
2 years old	2.13%	14.87%	-12.74pp*** (−3.47)	-22.33%	-8.60%	-13.72pp (−0.69)	14.25%	2.40%	11.85pp*** (8.37)
3 years old	-1.45%	6.94%	-8.39pp** (−2.10)	-26.13%	34.39%	-60.51pp** (−2.00)	13.64%	1.08%	12.56pp*** (8.16)
4 years old	-3.40%	3.59%	-6.98pp (−1.61)	-5.41%	2.65%	-8.05pp (−0.32)	14.10%	1.05%	13.05pp*** (7.30)
5 years old	-0.62%	6.54%	-7.15pp (−1.56)	-3.07%	-6.81%	3.73pp (0.17)	12.56%	-0.99%	13.55pp*** (7.11)
6–10 years old	-5.44%	4.71%	-10.15pp*** (−4.78)	-6.69%	-2.53%	-4.16pp (−0.41)	10.20%	-0.62%	10.82pp*** (12.35)
11–15 years old	-6.41%	0.18%	-6.59pp** (−2.03)	-16.85%	-10.64%	-6.21pp (−0.41)	9.50%	-0.63%	10.14pp*** (8.09)
16–20 years old	-8.44%	3.66%	-12.10pp*** (−3.47)	-5.86%	13.14%	-19.00pp (−1.10)	12.38%	4.24%	8.15pp*** (7.37)
>20 years old	-14.09%	-5.20%	-8.88pp*** (−5.49)	-10.17%	1.25%	-11.42pp (−1.63)	4.63%	1.70%	2.93pp*** (6.14)

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

Panel B – contin.

	Investor Category								
	Banks			Insurance Companies			Investment Advisors		
	Positive	Negative	$\Delta\, VBSI$	Positive	Negative	$\Delta\, VBSI$	Positive	Negative	$\Delta\, VBSI$
Firm Age Portfolio									
<1 year old	15.99%	8.00%	7.98pp**	19.80%	4.40%	15.40pp***	26.65%	7.03%	19.62pp***
			(2.28)			(3.36)			(8.01)
1 year old	21.83%	9.69%	12.14pp***	20.11%	3.26%	16.85pp***	17.99%	6.84%	11.16pp***
			(5.48)			(5.94)			(7.00)
2 years old	14.25%	1.92%	12.33pp***	10.37%	0.58%	9.79pp***	16.16%	6.24%	9.93pp***
			(5.30)			(3.28)			(5.81)
3 years old	12.48%	0.22%	12.27pp***	12.58%	2.59%	9.99pp***	15.38%	4.32%	11.06pp***
			(4.75)			(3.02)			(5.87)
4 years old	10.78%	-3.70%	14.48pp***	16.15%	6.02%	10.13pp***	16.76%	4.08%	12.69pp***
			(4.98)			(2.72)			(5.93)
5 years old	9.32%	-1.01%	10.33pp***	16.06%	-0.39%	16.45pp***	14.76%	2.66%	12.10pp***
			(3.44)			(4.13)			(5.30)
6–10 years old	9.81%	-1.79%	11.59pp***	13.45%	2.60%	10.85pp***	11.26%	2.59%	8.67pp***
			(8.22)			(5.76)			(8.06)
11–15 years old	8.14%	-5.00%	13.14pp***	11.58%	1.31%	10.26pp***	10.20%	2.62%	7.57pp***
			(6.38)			(3.75)			(4.84)
16–20 years old	11.83%	0.59%	11.24pp***	15.04%	8.81%	6.23pp**	11.49%	6.21%	5.28pp***
			(6.05)			(2.42)			(3.67)
>20 years old	2.61%	-3.20%	5.81pp***	7.55%	1.00%	6.55pp***	5.72%	2.86%	2.86pp***
			(6.53)			(5.61)			(4.46)

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

Panel B – contin.	*Investor Category*					
	Investment Companies			Other Large Institutional Investors		
	Positive	Negative	$\Delta VBSI$	Positive	Negative	$\Delta VBSI$
Firm Age Portfolio						
<1 year old	16.51%	-4.88%	21.39pp*** (5.78)	40.00%	19.69%	20.31pp*** (4.04)
1 year old	12.48%	-11.40%	23.88pp*** (9.62)	33.37%	33.27%	0.11pp (0.04)
2 years old	13.39%	-5.50%	18.89pp*** (6.98)	18.55%	18.09%	0.46pp (0.14)
3 years old	13.59%	-5.31%	18.90pp*** (6.31)	14.63%	9.22%	5.41pp (1.47)
4 years old	19.29%	-1.75%	21.04pp*** (6.13)	10.67%	8.85%	1.82pp (0.44)
5 years old	13.07%	-4.75%	17.82pp*** (4.79)	17.72%	6.42%	11.29pp** (2.56)
6–10 years old	12.61%	-7.64%	20.25pp*** (11.25)	15.26%	8.56%	6.71pp*** (3.22)
11–15 years old	15.38%	-2.77%	18.15pp*** (6.84)	10.49%	-0.32%	10.81pp*** (3.57)
16–20 years old	13.13%	-0.54%	13.67pp*** (5.20)	10.89%	11.89%	-1.00pp (−0.35)
>20 years old	10.78%	2.13%	8.65pp*** (7.23)	2.03%	1.93%	0.10pp (0.08)

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

investors do not seem to be primarily responsible for the higher stock return responsiveness to the negative earnings surprises among young/growth stocks, and hence for *AMOUES*. In fact, their contrarian trading tendencies rather attenuate such phenomenon. Similar conclusions for this investor class can be drawn from Panel B of Table 6.3. Interestingly, dependent on the *Firm Age* portfolio, we find evidence of both the contrarian-to-momentum behavior (consistent with e.g. Kaniel et al., 2012) and for the attention-driven buying (in line with e.g. Barber and Odean, 2008; Hirshleifer et al., 2008). In this regard, individuals appear to be net buyers (regardless of the sign of a surprise) of the youngest stocks (i.e. less than 3 years old) and contrarian investors for the rest of the stocks[5].

While examining the category of *Small Enterprises*, both for *BSI* and for *VBSI* ratios, we find very mixed, inconclusive results. Moreover, the vast majority of Δ*(V)BSI*'s are not statistically significant. Thus, it is not possible to identify any clear behavioral pattern for small institutional investors. Nonetheless, we do observe informative results among the largest institutional investors (ie. banks, insurance companies, investment companies, investment advisors, and other institutional investors).

When analyzing results for large institutions, we see that throughout all *Firm Age* portfolios of these investors (including young stocks), all *VBSI* ratios related to positive earnings surprises are always positive. For example, the volume based buy-sell imbalances for portfolios of 1-year-old firms experiencing positive surprise for *Banks*, *Insurance Companies*, *Investment Advisors*, *Investment Companies*, and *Other Large Institutional Investors* are respectively: 21.83%, 20.11%, 17.99%, 12.48%, and 33.37%. This finding is consistent with the expectation: when experiencing positive earnings surprises, institutional investors are more prone to acquire than to sell stocks.

However, contrary to expected, we do not find a negative sign on all the *VBSI*'s linked to negative earnings surprises, and, if present, the absolute magnitude of a *VBSI* with a negative sign associated with negative surprises is never larger than that of a *VBSI* linked to positive earnings news within the same *Firm Age* portfolio[6]. Thus, we do not explicitly observe an increased responsiveness to neg-

[5] with the exception of the *Firm Age* [$>$ 20 years old] portfolio
[6] with the exception of the *Banks* [$>$ 20 years old] portfolio

ative earnings surprises relative to the level of responsiveness to positive earnings surprises. This is not consistent with my expectations, but can be explained by the fact that the Thomson Reuters dataset used for calculating *VBSI* does not allow to detect trading activity around the proper earnings announcement (preannouncement) date. Since *VBSI* ratios related to positive surprises are always positive and higher than those related to negative surprises, we clearly see that institutions tend to purchase stocks linked to negative earnings surprises in a much lower degree than those associated with positive surprises. For instance, for the category of *Insurance Companies*, the volume based buy-sell imbalance is 10.37% if traded 2-year-old firms are experiencing positive surprises, and 0.58% if such firms are associated with negative surprises. This means that, on average, out of all the shares of a 2-year-old company experiencing a positive (negative) earnings surprise and traded by *Insurance Companies*, 10.37% (0.58%) of them constitutes a surplus of shares purchased over shares sold. Moreover, the statistical significance on Δ *VBSI* in all of *Firm Age* portfolios[7] indicates that the trading patterns for the opposite surprise signs are significantly different from each other. Therefore, although by comparing the magnitudes of *VBSI* ratios of institutions we are not able to confirm that institutional investors are more responsive to the negative earnings surprises of young firms, we do find an indirect evidence supporting this prediction. As trading tendencies of individuals clearly attenuate the impact of bad earnings news on stock prices, whereas institutional investors buy stocks related to negative earnings surprises to a much lesser extent than those linked to positive earnings surprises, out of these two groups, it appears more probable that institutions are the group that primarily drives the negative returns of young stocks and causes *AMOUES*.

Interestingly, among all the categories of large institutional investors, *Investment Companies* are associated with the highest values of Δ *VBSI*. Moreover, this category alone displays negative volume based buy-sell imbalances related to the negative earnings surprises in all except one *Firm Age* portfolio. These results suggest that *Investment Companies* are particularly prone to the momentum behavior around the earnings announcements.

As demonstrated in the earlier part of this chapter, the phenomena of the higher stock prices responsiveness to earnings surprises of young (growth) firms and the sub-

[7] with the exception of the *Other Large Institutional Investors* category

sequent gradual decline in this responsiveness throughout the consecutive years of company's existence on the stock market (lower growth classes) stem from the resolution of uncertainty about these firms' true profitability by investors. Therefore, if institutional investors do indeed learn about the actual stock profitability, we should observe a gradual decline in their overreaction to the earnings surprises throughout company's aging.

When comparing $\Delta\,VBSI$'s across all the $Firm\,Age$ portfolios within the same $Investor\,Category$ reported in Panel B of Table 6.3, we observe that all of large institutional investor groups display the overall decrease in absolute values of $\Delta\,VBSI$ for the older companies. For example, $\Delta\,VBSI$ of $Investment\,Advisors$ declines from 19.62pp for the portfolio [$<$ 1 year old], through 12.69pp for [4 years old], 8.67pp for [6–10 years old], and 5.28pp for [16–20 years old], to 2.86pp for [$>$ 20 years old]. This pattern suggests that institutional investors do learn about the true stock profitability during the earnings announcements. On the other hand, we do not observe such a trend among individuals. $\Delta\,VBSI$'s of this investor class for the equivalent $Firm\,Age$ portfolios are respectively: –11.94pp, –6.98pp, –10.15pp, –12.10pp, and –8.88pp.

Figure 6.2 provides an additional evidence on trading patterns of individuals and large institutional investors, as it plots their $\Delta\,VBSI$'s against each consecutive firm age. Moreover, it also plots the logarithmic trends in $\Delta\,VBSI$ for both investor classes. The graph clearly demonstrates a declining trend in $\Delta\,VBSI$ of institutional investors over the successive firm years. Once again, the results tell us that institutional investors do resolve uncertainty about stocks' profitability during earnings announcements. Conversely, the trend in $\Delta\,VBSI$ of individual investors is flat with seemingly random values of $\Delta\,VBSI$, suggesting that individual investors in general do not learn about stocks' true profitability.

Overall, the presented evidence supports the H4. Institutions display a superior ability to learn about stocks' actual profitability. When they are more uncertain about such stocks, they overreact more abruptly at the time of expectational revisions. This in turn results in the higher stock price responsiveness to the negative earnings surprises for young/growth companies, magnifies the return differential between growth and value stocks, and leads to $AMOUES$.

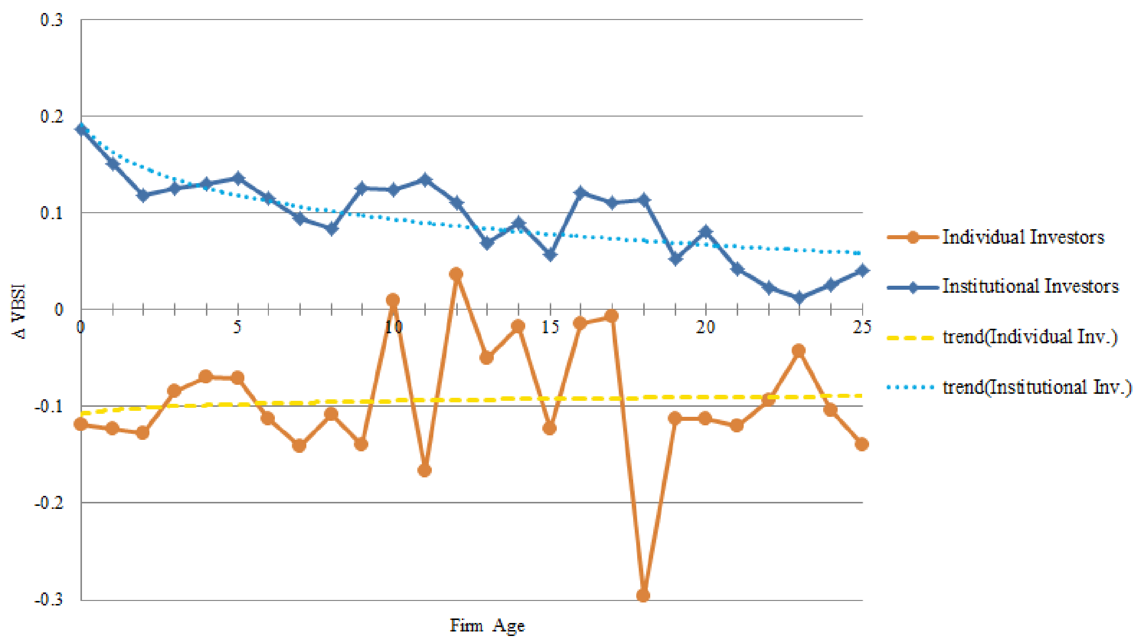

Figure 6.2: VBSI Differential related to Quarterly Earnings Announcements, by Investor Class

The graph plots $\Delta VBSI$ for individual and institutional investor classes against each *Firm Age* group. $\Delta VBSI$ denotes the differential between the mean Volume Buy-Sell Imbalance related to positive earnings surprises and the mean Volume Buy-Sell Imbalance related to negative earnings surprises. On the *Firm Age* axis, each value accounts for the company age on the forecast period end date (counting of age starts with the value of 0 on the IPO date). Additionally, the graph plots the logarithmic trends for both investor classes.

Having learned which investor class is more prone to trigger the asymmetry in responsiveness to earnings surprises, we can move on to the results of testing the H5. Table 6.4 presents *(V)BSI* ratios according to three levels of investor experience. Panel A reports *BSI* calculated from the number of trades. Similarly to the results for the whole sample of *Individuals* when testing the H4, we see that individual investors with the smallest trading experience (i.e. [1–50 trades]) are more prone to buy stocks experiencing negative earnings surprises than those linked to positive earnings surprises. For example, within the portfolio [< 1 year old], the buy-sell imbalance related to positive surprises is 17.12%, whereas that associated with negative surprises is 30.45%. When looking at Panel B of Table 6.4, we find analogous results for *VBSI* (i.e. 16.65% vs. 26.74%, respectively). Conversely, among the most

Table 6.4: Buy-Sell Imbalances related to Quarterly Earnings Announcements, by Investor Experience

Cumulative Number of Trades is a proxy for investor experience based on the cumulative number of trades assigned to an account performing such a trade (where [1–50 trades] accounts for the smallest experience). For every investor experience group, traded stocks are divided into subportfolios based on the sign (positive or negative) of an earnings surprise and based on the company age on the forecast period end date (counting of age starts with the value of 0 on the IPO date). For every *Firm Age* portfolio within the same investor experience group is calculated difference between *(V)BSI* for positive surprises and *(V)BSI* for negative surprises (with t-statistics in parentheses). Panel A presents results for the original *BSI* ratio, whereas Panel B contains results for the *VBSI* ratio.

Panel A - *BSI*

	Cumulative Number of Trades								
	1–50 trades			51–100 trades			>100 trades		
	Positive	Negative	ΔBSI	Positive	Negative	ΔBSI	Positive	Negative	ΔBSI
Firm Age Portfolio									
<1 year old	17.12%	30.45%	-13.33pp	1.15%	18.18%	-17.03pp	8.57%	-11.11%	19.68pp
			(−1.04)			(−0.61)			(0.69)
1 year old	10.78%	21.09%	-10.31pp	-9.52%	22.00%	-31.52pp*	-3.73%	-3.20%	-0.53pp
			(−1.23)			(−1.84)			(−0.03)
2 years old	6.94%	21.63%	-14.69pp*	-13.21%	-0.98%	-12.23pp	7.06%	6.28%	0.78pp
			(−1.67)			(−0.68)			(0.05)
3 years old	8.79%	26.66%	-17.87pp*	-13.95%	0.65%	-14.61pp	-8.20%	1.06%	-9.26pp
			(−1.88)			(−0.73)			(−0.50)
4 years old	-9.74%	23.56%	-33.30pp***	14.63%	-12.88%	27.51pp	5.77%	0.35%	5.41pp
			(−3.53)			(1.34)			(0.30)
5 years old	5.99%	12.88%	-6.89pp	-20.58%	32.68%	-53.26pp***	5.61%	2.03%	3.58pp
			(−0.71)			(−2.93)			(0.19)
6–10 years old	-5.74%	13.13%	-18.87pp***	1.21%	-13.44%	14.65pp	0.41%	-4.83%	5.24pp
			(−4.22)			(1.59)			(0.58)
11–15 years old	-9.71%	6.89%	-16.60pp**	-12.30%	-2.52%	-9.78pp	3.71%	15.48%	-11.77pp
			(−2.37)			(−0.75)			(−0.96)
16–20 years old	2.48%	19.00%	-16.52pp**	-27.93%	1.43%	-29.36pp	11.57%	-18.75%	30.32pp
			(−2.32)			(−1.37)			(1.53)
>20 years old	-5.38%	2.89%	-8.27pp**	-8.36%	-3.67%	-4.69pp	-9.33%	-12.33%	3.01pp
			(−2.46)			(−0.63)			(0.41)

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

Panel B - *VBSI*									
	Cumulative Number of Trades								
	1–50 trades			51–100 trades			>100 trades		
	Positive	Negative	Δ *VBSI*	Positive	Negative	Δ *VBSI*	Positive	Negative	Δ *VBSI*
Firm Age Portfolio									
<1 year old	16.65%	26.74%	-10.09pp	2.07%	18.18%	-16.11pp	8.14%	-8.33%	16.47pp
			(-0.78)			(-0.58)			(0.57)
1 year old	8.80%	19.71%	-10.91pp	-7.55%	21.33%	-28.88pp*	-4.68%	-5.18%	0.49pp
			(-1.28)			(-1.68)			(0.03)
2 years old	6.89%	21.56%	-14.67pp*	-14.34%	-1.95%	-12.39pp	5.55%	6.64%	-1.09pp
			(-1.66)			(-0.69)			(-0.07)
3 years old	8.95%	25.28%	-16.33pp*	-14.93%	-0.13%	-14.80pp	-7.62%	1.92%	-9.54pp
			(-1.69)			(-0.74)			(-0.51)
4 years old	-13.00%	24.71%	-37.70pp***	15.85%	-13.10%	28.95pp	3.29%	1.77%	1.51pp
			(-3.97)			(1.40)			(0.08)
5 years old	5.40%	12.26%	-6.85pp	-25.62%	32.37%	-58.00pp***	5.48%	-2.32%	7.80pp
			(-0.70)			(-3.16)			(0.41)
6–10 years old	-6.92%	13.21%	-20.12pp***	1.78%	-14.49%	16.27pp*	-0.33%	-7.47%	7.14pp
			(-4.41)			(1.76)			(0.78)
11–15 years old	-12.20%	7.67%	-19.87pp***	-12.80%	-5.88%	-6.92pp	3.80%	13.12%	-9.32pp
			(-2.81)			(-0.53)			(-0.75)
16–20 years old	0.97%	19.16%	-18.19pp**	-29.28%	1.62%	-30.90pp	12.43%	-22.04%	34.47pp*
			(-2.50)			(-1.44)			(1.73)
>20 years old	-6.27%	2.97%	-9.25pp***	-8.18%	-4.17%	-4.01pp	-8.81%	-12.42%	3.61pp
			(-2.68)			(-0.54)			(0.49)

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

experienced investors (i.e.[$>$ 100 trades]), consistent with the prediction, we find mostly the opposite tendency: more experienced individuals tend to buy stocks associated with negative earnings surprises in a lower degree than those experiencing positive earnings news. For instance, within the portfolio [$<$ 1 year old], the *BSI* ratio for the most experienced individual investors related to positive earnings surprises reported in Panel A of Table 6.4 is 8.57%, whereas that linked to negative earnings news is –11.11%. When looking at Panel B of Table 6.4, we find analogous results for *VBSI* (i.e. 8.14% vs. –8.33%, respectively). However, although we see that the predicted pattern is present in the results, we find that *p*-values stemming from *t*-statistics of Δ*(V)BSI*'s are high, and thus not that significant.

Overall, the results of my analysis provide insufficient support for the H5. We do not find an explicit evidence that more experienced individual investors learn about stocks' true profitability during earnings announcements. Even if some of them indeed resolve uncertainty, the impact of their trades on stock returns is rather minor compared to the whole population of individual investors. Nonetheless, such a finding provides additional support for the idea that institutions are the investor group primarily responsible for the overreaction to the negative earnings surprises among growth stocks.

Chapter 7

Conclusions

In this thesis I investigate investor reactions to earnings announcements from a learning perspective. Specifically, I examine whether the higher impact of negative earnings surprises on stock returns of growth (glamour) firms stems from a higher level of uncertainty about these stocks' profitability. In this regard I formulate five hypotheses based on the intuition drawn from related financial literature. First hypothesis tests whether investors truly resolve their uncertainty during earnings announcements. I assume that the impact of earnings surprises on the stock returns of a firm decreases over time due to investors' learning about such firm's true profitability. Second and third hypotheses investigate whether the increased overreaction to negative surprises arises out of a higher level of uncertainty. I start by using the company age as a proxy for uncertainty, and thereafter include into my analysis the firm size as an additional proxy. I hypothesize that stock price responsiveness to negative earnings surprises of younger firms is higher than that associated with positive surprises, and I expect such an asymmetry to decrease with company's aging due to investors' learning. Moreover, I predict that this pattern will be more pronounced among the smallest firms since they bear more uncertainty. Fourth and fifth hypotheses investigate who mainly overreacts to negative earnings surprises of the stocks related to a higher level of uncertainty. I assume that institutional investors are the investor class primarily more responsive to earnings surprises of young/growth stocks in the direction of a surprise due to their superior ability to learn about stock profitability. However, I expect individual investors to display similar trading behavior as they gain more experience.

As expected, results of the tests confirm that as companies age, their stock returns become gradually less affected by earnings surprises. Therefore, investors appear to indeed resolve uncertainty about stocks' true profitability during quarterly earnings announcements. Moreover, in line with predictions, the impact of negative earnings surprises on stock returns of younger firms is significantly higher than that of positive surprises, and this asymmetry declines over company's aging. When accounting for the firm size, the observed pattern results to be most pronounced in the subsample of the smallest companies. These findings thereby confirm that the overreaction to negative earnings surprises is remarkably correlated with the uncertainty about stocks' true profitability.

Second part of the analysis examines reactions to earnings announcements from the perspective of particular investor categories. In line with expectations, institutional investors appear to be the investor group that primarily overreacts to earnings surprises in the direction of their sign. Around earnings announcements, institutional investors display the momentum behavior, whereas reverse trading patterns are observed for individual investors. Moreover, the decreasing differential in the institutional investors' reaction to the opposite surprise signs over the course of company's aging indicates that this investor class does indeed resolve their uncertainty about stocks' actual profitability during earnings announcements. No such pattern is observed among trades of individual investors. Finally, results reveal very weak, if any, support for the notion that individual investors learn about stocks' true profitability as they gain more experience. Thus, primarily more sophisticated investors tend to overreact to earnings surprises of young firms due to resolving uncertainty about their actual prospects. As these investors learn more on this issue during the subsequent earnings announcements, their reactions become milder.

Overall, results of the analyses conducted in this thesis are consistent with the learning perspective. Figure 7.1 presents a simplified scheme of the inferred cause-and-effect process leading to the return differential between growth and value stocks and leading to *AMOUES*. The scheme is created based on the insights from past financial literature and on the evidence from this study. Evidence of Pástor and Veronesi (2003) implies that growth stocks are associated with a higher level of uncertainty. As the level of uncertainty about stock profitability is higher, the bias in analysts' forecasts is also higher. If such forecasts are auspicious, investors become

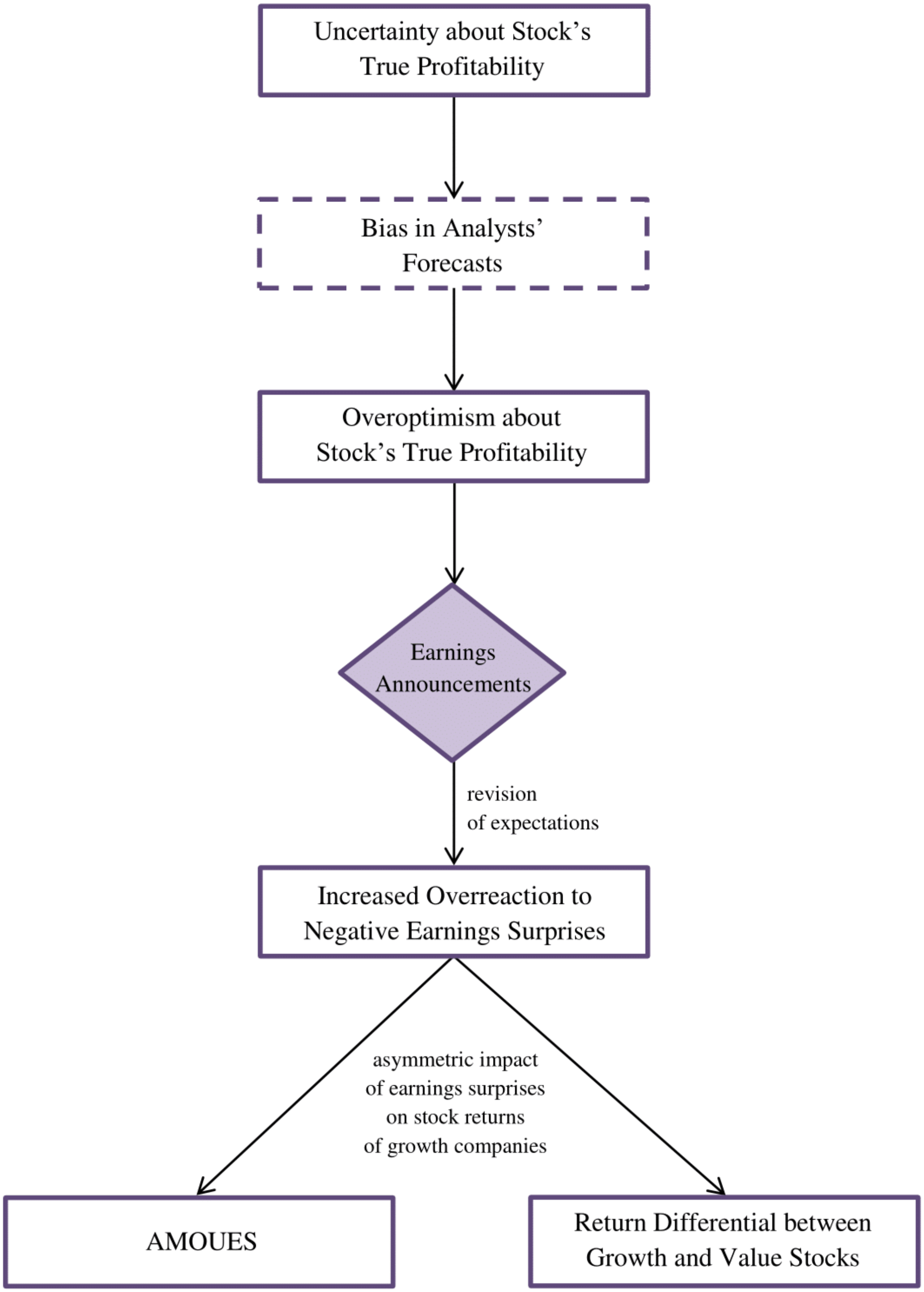

Figure 7.1: Inferred Cause-and-Effect Process Leading to the Return Differential between Growth and Value Stocks

The figure presents simplified scheme of the inferred cause-and-affect process leading to the return differential between growth (glamour) and value stocks. The scheme is created based on the insights from past financial research and the results of this thesis.

overly optimistic about the relevant stocks. Results of the research of La Porta (1996) and Dechow and Sloan (1997) show that analysts' forecasts of growth stocks are on average excessively optimistic. On the other hand, because of Bayesian updating, an expectational revision has bigger impact on the prior belief when the uncertainty is higher (see equations 2.1–2.3). Thus, overoptimism may also arise due to extrapolating the initial successful performance of young/growth stocks into the future by mere investors, in line with the intuition of Lakonishok et al. (1994). Furthermore, the larger the uncertainty, the higher the impact of a negative earnings surprise on the current stock returns of a relevant firm. Thus, since growth firms are associated with a higher level of uncertainty, and since the beliefs about their prospects are on average overly optimistic, their average stock returns are affected more by the negative earnings surprises. This in turn enhances the formation of the return differential between growth and value stocks and $AMOUES$.

Results of my study challenge the view of Lakonishok et al. (1994) that investors overreacting to good/bad news are naïve, and thereby that the return differential between growth and value stocks arises due to such naivety. Contrary to that, my findings suggest that such investors are sophisticated and well informed, and that the return differential stems from resolving uncertainty about stocks' true profitability. The notion of uncertainty about stock profitability explains also why other two phenomena reported in the financial research arise, such as the lower level of accuracy in the analysts' forecasts regarding smaller stocks (see Brown et al., 1987) and the higher return differential between growth and value stocks in the subsample of the smallest firms (see La Porta et al., 1997). Interestingly, dependent on the firm age category, I find evidence for both contrarian-to-momentum behavior (consistent with e.g. Kaniel et al., 2012) and attention-driven buying (in line with e.g. Barber and Odean, 2008; Hirshleifer et al., 2008) in the trading patterns of individual investors. Further research could explore in more detail the switch between the former and the latter investment behaviors.

My research is subject to several limitations. First, the sample representing individual investors accounts only for the trades of clients of a large discount brokerage firm. I cannot rule out the possibility that investors registered at other brokerage firms perform their trades in a different way. Hence, it may be an incomplete representation of the trading pattern of an average individual investor. Second, since

Thomson Reuters allows to examine only the net change in common stocks held by institutions at the end of a calendar quarter, I cannot analyze the patterns in stock purchases and sales of this group during the exact *postret* interval. Thus, their buy-sell imbalances are prone to be contaminated by other influential events and should be treated rather as an approximation of general trends. Third, since my data solely consists of trading instances coming from the US stock market, my hypotheses may need to be further tested on stock markets in other countries to verify the generalization of my findings.

Appendix A

Robustness Tests

A.1 Wald Test for Difference in Coefficients

Table A.1: Estimated Statistics of the Wald Test for $H_0 : \beta_i - \beta_j = 0$

Table below presents t-statistics of the Wald Test, that enable us to check whether the difference between the response coefficients is statistically significant as suggested by the corresponding hypotheses.

	H1	H2	H3 – $SIZE$				
			1	2	3	4	5
β_3 $vs.$ β_1 ($SURP. * AGE$ vs. AGE)	17.71***						
β_3 $vs.$ β_2 ($SURP. * AGE$ vs. $SURPRISE$)	7.28**						
β_2 $vs.$ β_3 ($GOOD$ vs. BAD)		56.71***	24.78***	29.37***	28.28***	27.75***	25.25***
β_4 $vs.$ β_5 ($GOOD * AGE$ vs. $BAD * AGE$)		14.37***	4.86***	3.46**	2.53*	2.04	3.23**
$\|\beta_2\|$ $vs.$ $\|\beta_3\|$ ($\|GOOD\|$ vs. $\|BAD\|$)		2.91**	1.49	2.23*	0.06	0.79	1.29
$\|\beta_4\|$ $vs.$ $\|\beta_5\|$ ($\|GOOD * AGE\|$ vs. $\|BAD * AGE\|$)		-2.28*	-2.96**	-0.73	0.87	-0.45	-0.29

Controlling for two-tailed p-values, ***, **, * indicate respectively 1%, 5%, and 10% significance levels.

A.2 Robustness of $\epsilon_{i,t}$ for Linear Regressions

Table A.2 is to verify the assumption that the linear regressions carried out are unbiased, which is a fundamental assumption of *GLM* models. My tests indeed verify with high confidence that the regressions carried out had no bias since the values of t-statistics are very low.

Table A.2: Estimated Statistics of t-test for $H_0 : e_{i,t} = 0$

Table below presents the results of t-test for $H_0 : e_{i,t} = 0$ performed for each regression. The first column displays the estimated value of t-statistics for the hypothesis H1, the next one for the hypothesis H2 and the last five for the hypothesis H3 (where 1 denotes the smallest-firm-quintile and 5 denotes the largest-firm-quintile).

H1	H2	H3 – $SIZE$				
		1	2	3	4	5
-3.51e-08	4.89e-08	1.39e-07	-2.09e-07	-1.92e-07	-3.9e-07	3.5e-08

A.3 Inspection of Heteroscedasticity

In order to inspect the presence of heteroscedasticity among the variables used in the regressions, I plot the regression residuals vs. the dependent variable to examine the magnitude of dispersion of the former against the latter. As follows in the plots below, the residual terms' scale is homogeneously distributed across different values of the dependent variable. However, to be confident that the regression results are robust, I employ the White-Huber Technique adjusting the standard errors of the estimated coefficients in my regressions, as indicated in the Methodology part.

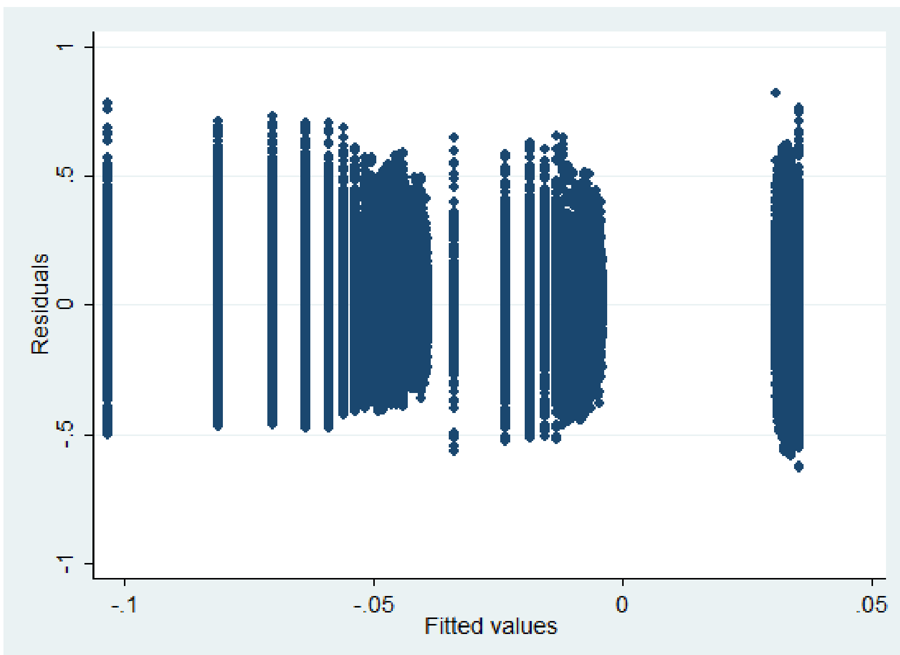

Figure A.1: Dispersion of Residual Term across BHAR for Hypothesis H1

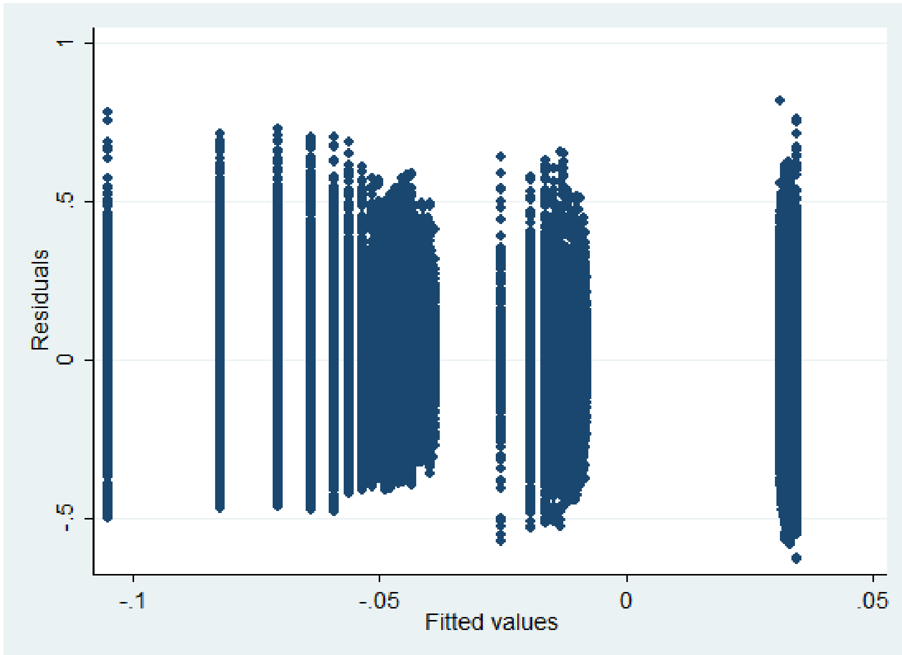

Figure A.2: Dispersion of Residual Term across BHAR for Hypothesis H2

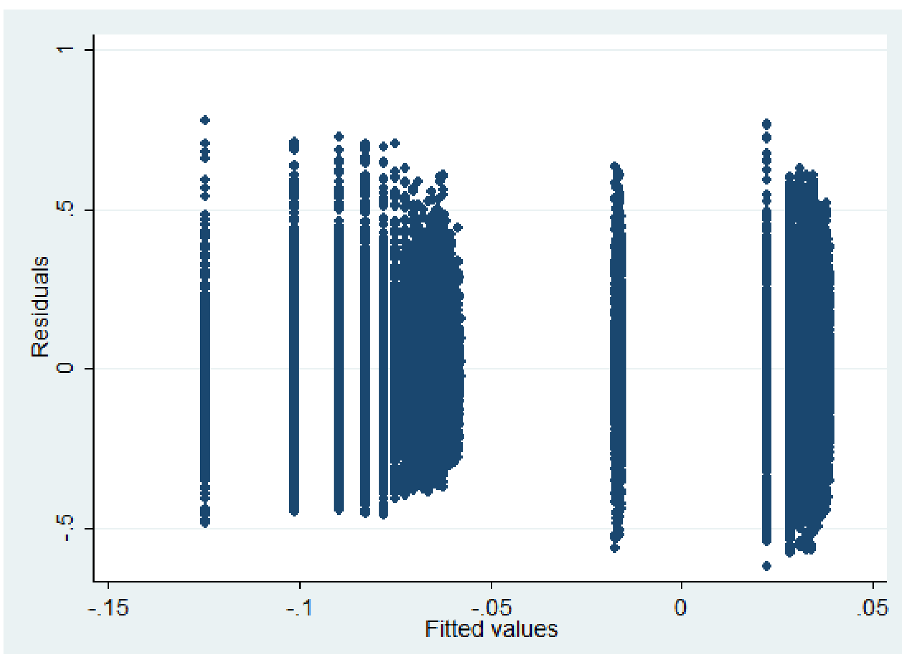

Figure A.3: Dispersion of Residual Term across BHAR for Hypothesis H2 with $SIZE = 1$

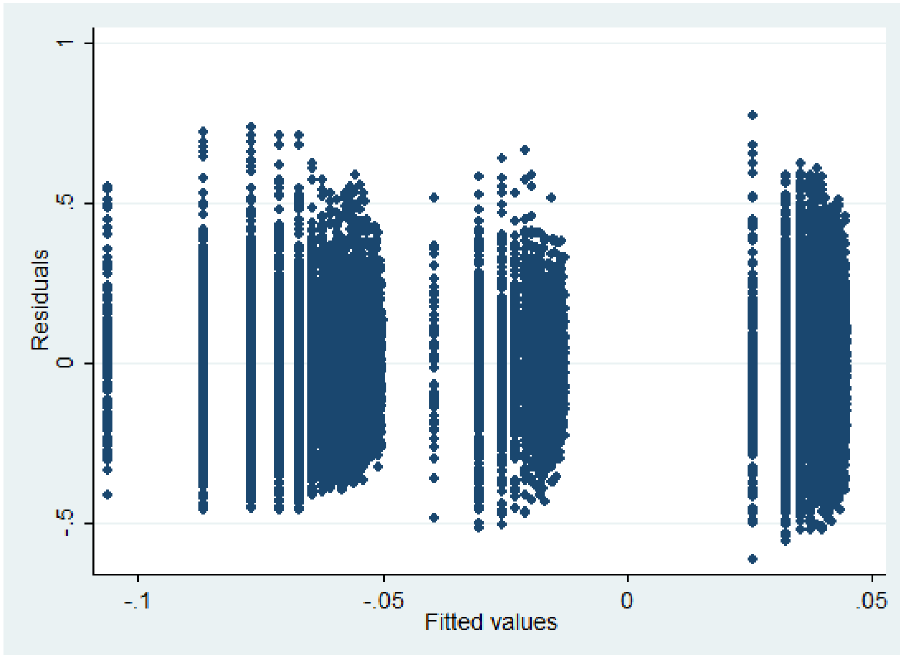

Figure A.4: Dispersion of Residual Term across BHAR for Hypothesis H2 with $SIZE = 2$

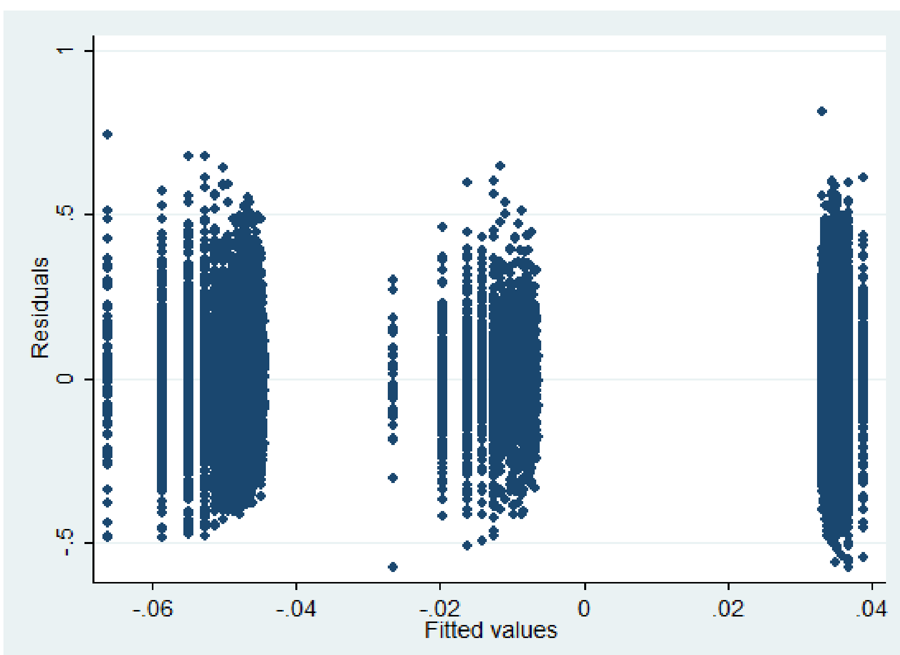

Figure A.5: Dispersion of Residual Term across BHAR for Hypothesis H2 with $SIZE = 3$

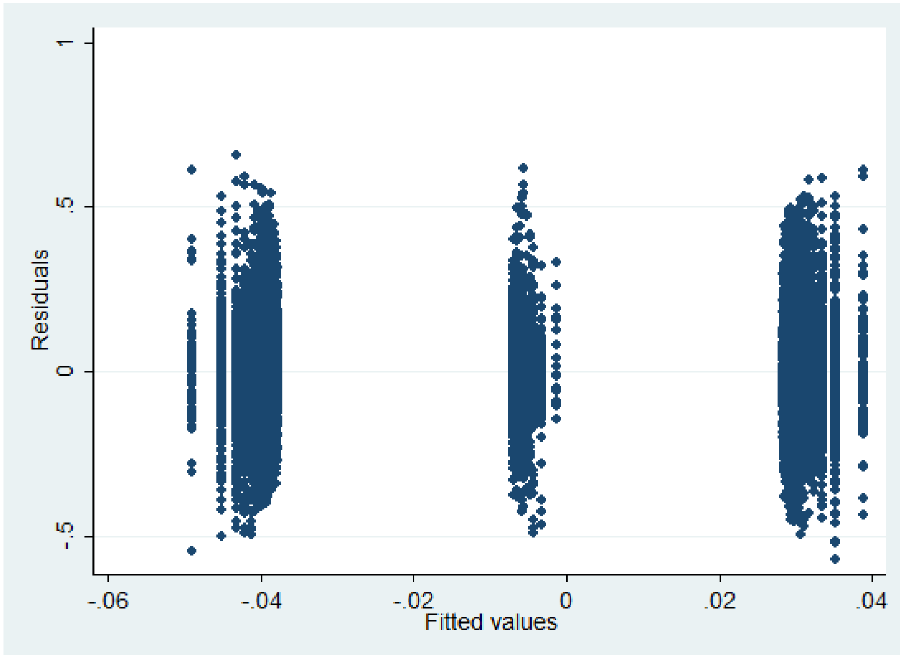

Figure A.6: Dispersion of Residual Term across BHAR for Hypothesis H2 with $SIZE = 4$

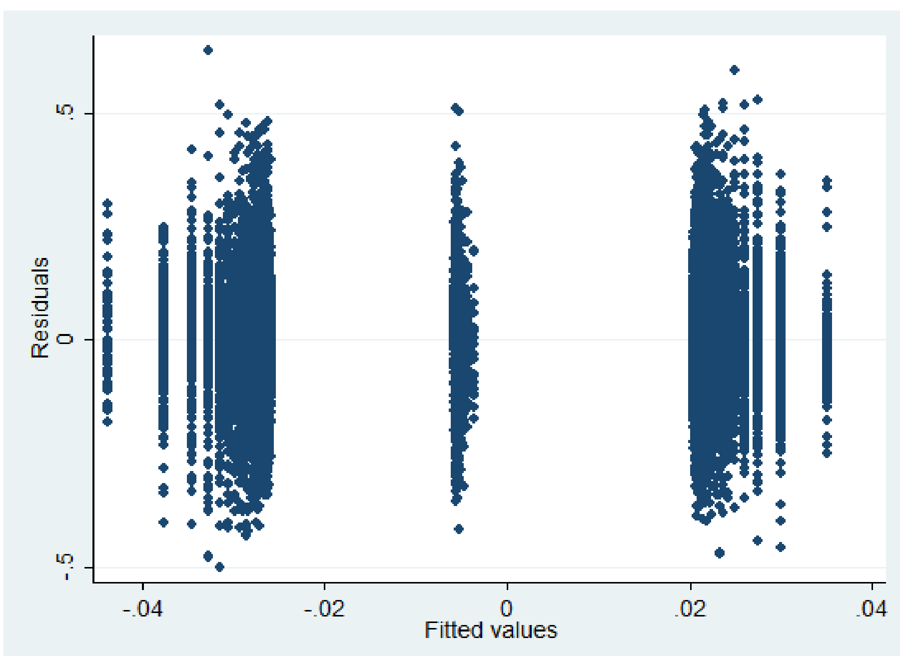

Figure A.7: Dispersion of Residual Term across BHAR for Hypothesis H2 with $SIZE = 5$

Appendix B

STATA Code

```
cd "C:\Users\Agnieszka\Documents\EUR_Masters_Thesis"

* EXTRACTING DATA RELATED TO EPS FORECASTS AND TO THE SUBSEQUENT
   ↪ SURPRISES:
* trimming the data for the examined period and dropping the
   ↪ incomplete observations (essentially for the Estimation Window,
   ↪  a 2-year margin following the examined period is included):
use IBES_1989-2012, clear
drop fpi ticker measure meanest
drop if missing(cusip)
format anndats_act %td
drop if anndats_act<td(1,1,1991) | anndats_act>td(31,12,2012)
drop if anndats_act==. | actual==. | fpedats==.

* dropping the forecasts made after the end of the Forecast Period &
   ↪ selecting the value of the last available Median Forecast
   ↪ before this date as the Forecast EPS:
format statpers %td
format fpedats %td
drop if statpers>fpedats
sort cusip anndats_act fpedats statpers
by cusip anndats_act: keep if _n==_N
```

```
drop statpers

* generating SURPRISE dummies & basic variables:
gen surprise_value=actual-medest
gen SURPRISE=1 if surprise_value>0
replace SURPRISE=-1 if surprise_value<0
replace SURPRISE=0 if surprise_value==0
gen GOOD = (SURPRISE>0)
gen BAD = (SURPRISE<0)
label var SURPRISE "1=pos, -1=neg, 0=no surpr"
label var GOOD "dummy for positive surprise"
label var BAD "dummy for negative surprise"
drop actual medest
gen frcst_qtr=qofd(fpedats)
gen id=cusip+string(frcst_qtr,"%tq")
drop frcst_qtr
gen yr_qtr = qofd(fpedats)+1
label var yr_qtr "Year & Quarter of Earnings Announcement"
format yr_qtr %tq

* controlling for multiple Forecast Periods within the same Calendar
   ↪ Quarter related to a single CUSIP and choosing the most recent
   ↪ one (apparently the related company had changed fiscal year
   ↪ specifications):
gsort id -fpedats
quietly by id: gen dup=cond(_N==1,0,_n)
drop if dup>1
drop dup

* droppping the erroneous observations, where quarterly Earnings
   ↪ Announcements occur with at least one quarter delay:
drop if anndats_act-fpedats>92
save IBES_1990-2012, replace
```

```
***************************

* EXTRACTING DATA RELATED TO QUARTERLY CHARACTERISTICS OF THE
   ↪ EXAMINED COMPANIES:
* trimming the data for the examined period and generating basic
   ↪ variables:
use COMPUSTATqtr_1989-2012.dta
format datadate %td
drop if datadate<td(31,12,1990)| datadate>=td(1,1,2011)
gen fisc_qtr = quarterly(datafqtr, "YQ")
drop datafqtr
format fisc_qtr %tq
gen dataqtr = quarterly(datacqtr, "YQ")
drop datacqtr
replace dataqtr=qofd(datadate) if missing(dataqtr)
format dataqtr %tq
format fyearq %ty
drop datadate
rename cusip cusip_compustat
gen cusip = substr(cusip_compustat, 1, 8)
drop cusip_compustat
gen id=cusip+string(dataqtr,"%tq")
gen yr_qtr = dataqtr+1
format yr_qtr %tq
label var yr_qtr "Year & Quarter of Earnings Announcement"
drop dataqtr

* dropping multiple observations on a single CUSIP related to the
   ↪ same Calendar & Fiscal Quarter:
sort cusip yr_qtr
quietly by cusip yr_qtr: gen dup=cond(_N==1,0,_n)
drop if dup>0
```

```
drop dup
sort cusip fisc_qtr
quietly by cusip fisc_qtr: gen dup=cond(_N==1,0,_n)
drop if dup>0
drop dup

* completing the missing quarterly accounting data of a company by referring for simplicity to the available information disclosed at the end of the relevant Fiscal Year or to the mean of Half-Year Disclosures:
sort gvkey fyearq
by gvkey fyearq: egen new_aqaq=mean(aqaq)
replace aqaq=new_aqaq if atq==.
by gvkey fyearq: egen new_prstkccy=mean(prstkccy)
replace prstkccy=new_prstkccy if atq==.
by gvkey fyearq: egen new_atq=mean(atq)
replace atq=new_atq if atq==.
drop gvkey fyearq fisc_qtr new_aqaq new_prstkccy new_atq
save COMPUSTATqtr_1990-2010, replace

***************************

* EXTRACTING DATA RELATED TO STOCK PRICES:
* selecting the data only related to the Common Stock, extracting the dates of companies' First Appearances in the CRSP Register & trimming the data for the examined period:
use CRSP_1925-2012, clear
drop if prc==.
keep if shrcd==10 | shrcd==11
drop shrcd
egen date_first = min(date), by(permco)
format date_first %td
label variable date_first "First Appearance in CRSP Register"
```

```
drop if date<=td(31,5,1990) | date>td(30,6,2012)

* calculating the Market Capitalization of companies at the beginning of a Calendar Quarter (based on the mean estimate of Market Capitalization during the first available week of a Calendar Quarter) - position relevant for the further creation of the decile portfolios:
gen market_value=(abs(prc)*shrout/1000)
sort permco date
by permco date: egen m_capd=sum(market_value)
label variable m_capd "Daily Market Capitalization (in mln)"
drop permno shrout market_value
format date %td
gen data_week = wofd(date)
format data_week %tw
sort permco data_week
by permco data_week: egen m_capw=mean(m_capd)
gen yr_qtr = qofd(date)
format yr_qtr %tq
label var yr_qtr "Year & Quarter"
sort permco yr_qtr
by permco yr_qtr: egen first_weekq=min(data_week)
format first_weekq %tw
replace m_capw=. if data_week!=first_weekq
by permco yr_qtr: egen m_capq=min(m_capw)
drop permco m_capd data_week m_capw first_weekq
label var m_capq "Market Capitalization (in mln) at the beginning of the quarter"
save CRSP_1990-2012, replace

****************************
```

```
* CREATING A BUSINESS CALENDAR BASED ON THE TRADING DAYS IN THE CRSP
   ↪ DATASET:
use CRSP_1990-2012, clear
drop if date<td(1,10,1990)
keep date
sort date
by date: keep if _n==1
bcal create crsp, from(date)

****************************

* FORMATTING THE DATASET WITH 3-MONTH TREASURY BILL RATES:
clear all
import excel TB3MS.xls, sheet("FRED Graph") firstrow
gen rf_rate=((1+TB3MS/100)^(1/360))-1
gen yr_m = mofd(observation_date)
format yr_m %tm
label var yr_m "Year & Month"
label var rf_rate "3-month Treasury Bill rate"
drop TB3MS observation_date
save 3M_TREASURY_BILL, replace

****************************

* MERGING DATASETS FOR THE REGRESSION ANALYSIS:

*** combining the CRPS, COMPUSTAT & I/B/E/S datasets ***
* extracting from the CRSP dataset the variables essential for
   ↪ calculating the Firm Age:
use CRSP_1990-2012, clear
drop date prc retx m_capq
sort cusip yr_qtr
by cusip yr_qtr: keep if _n==1
```

```
* merging with the COMPUSTAT dataset:
merge 1:1 cusip yr_qtr using COMPUSTATqtr_1990-2010, keep (match)
drop _merge

* merging with the I/B/E/S dataset & trimming the data for the
   ↪ examined period:
merge m:1 id using IBES_1990-2012, keep (match)
drop _merge id comnam conm cname surprise_value
drop if anndats_act<td(1,1,1991) | anndats_act>=td(1,1,2011)

* generating the AGE variable (in case of a missing IPO Date in
   ↪ COMPUSTAT, the date of First Appearance in the CRSP Register is
   ↪  applied; if both are available, the earlier is chosen):
format ipodate %td
replace date_first=ipodate if ipodate<date_first
drop ipodate
gen yearborn = yofd(date_first)
gen yeardata = yofd(fpedats)
gen firm_age = yeardata-yearborn
gen AGE=1/(2+firm_age)
drop if date_first>fpedats
drop yearborn yeardata date_first
label var firm_age "Company Age since the First Record in Common
   ↪ Stock Databases"
label var AGE "the reciprocal of 2 plus the Firm Age"

* dropping the observations that coincide with the M&A Activity and
   ↪ with the Stock Repurchases:
replace aqaq=0 if aqaq==.
replace prstkccy=0 if prstkccy==.
drop if aqaq!=0 | prstkccy!=0
drop aqaq prstkccy
```

```
* creating a variable essential for the further merging:
sort cusip anndats_act
by cusip: gen set=_n
sort cusip set
save merged_IBES+COMPUSTAT, replace

*** formatting the CRSP dataset ***
* reducing the CRSP dataset to the sample containing only CUSIPs in
   ↪ common with the I/B/E/S and COMPUSTAT datasets:
use merged_IBES+COMPUSTAT, clear
by cusip: keep if set==_N
keep cusip set
merge 1:m cusip using CRSP_1990-2012, keep (match)
drop _merge comnam prc date_first
rename set anncount

* generating the daily MARKET RETURN based on the decile portfolios
   ↪ of Market Capitalization at the beginning of each Quarter:
egen M_CAP10 = xtile(m_capq), by(yr_qtr) nq(10)
sort date M_CAP10
label var M_CAP10 "Market Capitalization Decile Portfolio (by quarter
   ↪ )"
by date M_CAP10: egen MKT_RET=mean(retx)
label var MKT_RET "Size-matched Market Return"
drop m_capq M_CAP10
save CRSP_1990-2012_adjusted, replace

*** operations essential to obtain a sufficient trading-day margin
   ↪ around Earnings Announcements ***
use CRSP_1990-2012_adjusted, clear
keep date cusip anncount
sort cusip
```

```
expand anncount
drop anncount
sort cusip date
by cusip date: gen set=_n
save CRSP_expanded, replace
use merged_IBES+COMPUSTAT, clear
keep anndats_act fpedats cusip set
sort cusip set
merge 1:m cusip set using CRSP_expanded, keep (match)
drop _merge
drop if anndats_act-date>92 | anndats_act-date<-730
sort cusip set
egen group_id = group(cusip set)
drop set
gen yr_qtr = qofd(date)
format yr_qtr %tq
label var yr_qtr "Year & Quarter"
save EVENTS_raw, replace

*** preparation of a complete dataset for the Regression Analysis ***
* extracting all the available Earnings Announcement & Forecast
   ↪ Period End dates related to a single CUSIP:
use IBES_1990-2012, clear
keep cusip anndats_act yr_qtr fpedats
rename anndats_act anndats_qtr
rename fpedats fpedatq
label var anndats_qtr "Announcement Date by Quarter"

* associating the extracted Earnings Announcement & Forecast Period
   ↪ End dates with the Quarters surrounding the examined Earnings
   ↪ Announcement observations:
merge 1:m cusip yr_qtr using EVENTS_raw, keep (match)
drop _merge yr_qtr
```

```
* creating a variable containing Year & Quarter of the examined
   ↪ Earnings Announcement observations (in contrast to the year &
   ↪ quarter based on the true date) - variable essential for
   ↪ further merging:
gen ann_qtr = qofd(fpedats)+1
label var ann_qtr "Year & Quarter of Earnings Announcement"
format ann_qtr %tq

* dropping from the estimation period the subsequent ‘‘postret’’
   ↪ intervals occurring over the course of two years following the
   ↪ examined Earnings Announcement observations (in order to avoid
   ↪ the excessive reduction of trading days within the estimation
   ↪ period, subsequent ‘‘postret’’ intervals start on the Forecast
   ↪ Period End date instead of 12 days before this date; in case
   ↪ the last day of the subsequent ‘‘postret’’ occurs during a non-
   ↪ business day, it is converted to the first available business
   ↪ day following that date):
gen end_wndw=.
replace end_wndw=anndats_qtr+1 if anndats_qtr>anndats_act
format end_wndw %td
replace fpedatq=. if end_wndw==.
forvalues i = 1/3 {
gen trd_date=bofd("crsp", end_wndw)
replace end_wndw=end_wndw+1 if trd_date==.
drop trd_date
}
sort group_id date
forvalues i = 1/7 {
by group_id: egen end_sbsq_wndw=min(end_wndw)
by group_id: egen sbsq_fpedat=min(fpedatq)
drop if date>=sbsq_fpedat & date<=end_sbsq_wndw & end_sbsq_wndw!=.
replace fpedatq=. if end_wndw<=end_sbsq_wndw
```

```
replace end_wndw=. if end_wndw<=end_sbsq_wndw
drop end_sbsq_wndw sbsq_fpedat
}
by group_id: egen sbsq_fpedat=min(fpedatq)
drop if date>=sbsq_fpedat & sbsq_fpedat!=.
drop sbsq_fpedat fpedatq anndats_qtr end_wndw

* coinciding the Earnings Announcement & Forecast Period End dates of
   ↪  the examined observations from I/B/E/S with the trading
   ↪ records from CRSP (in case an Earnings Announcement occurs
   ↪ during a non-business day, in order to maintain the Event
   ↪ Window ending 1 trading day after the Earnings Announcement
   ↪ Date, it is converted to the first available business day
   ↪ preceding that date; in case the Forecast Period End occurs
   ↪ during a non-business day, in order to maintain the Event
   ↪ Window starting 12 trading days before the Forecast Period End,
   ↪  it is converted to the first available business day following
   ↪ that date); dropping the observations that do not coincide with
   ↪  any trading date in CRSP for the relevant CUSIP:
gen anndats_adj=anndats_act
format anndats_adj %td
label var anndats_adj "Announcement Date Adjusted"
forvalues i = 1/3 {
gen trd_date=bofd("crsp", anndats_adj)
replace anndats_adj=anndats_adj-1 if trd_date==.
drop trd_date
}
gen trd_date=bofd("crsp", anndats_adj)
drop if trd_date==.
drop trd_date
forvalues i = 1/3 {
gen trd_date=bofd("crsp", fpedats)
replace fpedats=fpedats+1 if trd_date==.
```

```
drop trd_date
}
gen trd_date=bofd("crsp", fpedats)
drop if trd_date==.
drop trd_date
sort group_id date
by group_id: gen day_count=_n
gen event=day_count if date==anndats_adj
by group_id: egen e_day=min(event)
drop event
drop if e_day==.
gen end_qtr=day_count if date==fpedats
by group_id: egen endq_day=min(end_qtr)
drop end_qtr
drop if endq_day==.

* extracting the Event Window:
gen start=endq_day-12
drop if start<1
drop if day_count<start
gen end=e_day+1
gen window_width= e_day-endq_day+1+1+12
drop if window_width<3
by group_id: gen event_window=1 if day_count>=start & day_count<=end
replace event_window=0 if event_window==.
drop endq_day start end day_count e_day

* merging with the full adjusted CRSP dataset (previously reduced in
   ↪ order to maximize the speed of computer processing) & dropping
   ↪ the observations with missing returns during the Event Window:
merge m:1 cusip date using CRSP_1990-2012_adjusted, keep (match)
drop _merge anncount
sort group_id date
```

```
by group_id: gen missing_evret=1 if retx==. & event_window==1
by group_id: egen sum_missingevret=sum(missing_evret)
drop if sum_missingevret>0
drop missing_evret sum_missingevret

* dropping the missing returns within the Estimation Window (if there
    ↪  are missing returns during the Estimation Window, but not
    ↪ during the Event Window, such an observation is preserved):
drop if missing(retx)

* extracting the Estimation Window of the 180 earliest trading days
    ↪ following the Event Window & the Calendar Length of Estimation
    ↪ Window; dropping the observations with an Estimation Window
    ↪ shorter than the predefined length:
sort group_id date
by group_id: gen day_count=_n
by group_id: gen max = window_width+180
drop if day_count>max
gen max_date=date if day_count==max
by group_id: egen last_est_day=min(max_date)
gen cal_est_wndw=last_est_day-anndats_adj
label var cal_est_wndw "Calendar Length of Estimation Window+1"
drop max max_date last_est_day
by group_id: gen estim_window=(event_window==0)
by group_id: egen sum_estimwindow=sum(estim_window)
drop if sum_estimwindow<180
drop sum_estimwindow
save EVENTS_estim180, replace

* calculating Betas:
use EVENTS_estim180, clear
*by group_id: reg retx MKT_RET if estim_window==1
keep if estim_window==1
```

```
keep group_id retx MKT_RET day_count
tsset group_id day_count
rolling _b, window(180) saving (betas_estim180, every(1000) replace)
    ↪ keep(day_count): regress retx MKT_RET

* merging observations with Betas, 3-month Treasury Bill rates and
    ↪ calculating the Expected Return:
use EVENTS_estim180, clear
merge m:1 group_id using betas_estim180
drop _merge window_width cal_est_wndw start end _b_cons
gen yr_m = mofd(date)
format yr_m %tm
merge m:1 yr_m using 3M_TREASURY_BILL, keep (match)
drop _merge yr_m
gen Er_i=rf_rate+_b_MKT_RET*(MKT_RET-rf_rate)
label var Er_i "Expected Return for Company 'i' on a Day 't'"
drop estim_window yr_qtr MKT_RET rf_rate _b_MKT_RET anndats_adj

* merging with the full I/B/E/S+COMPUSTAT dataset (previously reduced
    ↪  in order to maximize the speed of computer processing):
rename ann_qtr yr_qtr
merge m:1 cusip yr_qtr using merged_IBES+COMPUSTAT, keep (match)
keep if event_window==1
drop _merge cusip anndats_act fpedats set event_window

* generating interaction terms:
gen SURPRISExAGE=SURPRISE*AGE
gen GOODxAGE=GOOD*AGE
gen BADxAGE=BAD*AGE

* calculating Buy-and-Hold Abnormal Returns:
xtset group_id day_count
gen BH1_ri = retx+1
```

```
by group_id: gen double BH_realized = BH1_ri if _n==1
by group_id: replace BH_realized = L.BH_realized*BH1_ri if _n>1
gen BH1_Eri=Er_i+1
by group_id: gen double BH_normal = BH1_Eri if _n==1
by group_id: replace BH_normal = L.BH_normal*BH1_Eri if _n>1
gen BHAR = BH_realized - BH_normal
label var BHAR "Buy-and-Hold Abnormal Return"
by group_id: keep if _n==_N
drop day_count

*dropping the observations where Firm Age>60:
drop if firm_age>60

*windsorising the Firm-Age porfolios:
egen BHAR100 = xtile(BHAR), by(firm_age) nq(100)
drop if BHAR100==100 | BHAR100==1

* conducting Regressions and Tests for the Hypotheses 1 & 2:
reg BHAR AGE SURPRISE SURPRISExAGE, robust
rvfplot
estat vce
predict e1, residual
egen avg_e1=mean(e1)
gen n=_N
egen sd_e1=sd(e1)
gen var_e1=(sd_e1)^2
gen t_test_e1=avg_e1/sqrt(var_e1/n)
drop e1 avg_e1 sd_e1 var_e1
reg BHAR AGE GOOD BAD GOODxAGE BADxAGE, robust
rvfplot
estat vce
predict e2, residual
egen avg_e2=mean(e2)
```

```
egen sd_e2=sd(e2)
gen var_e2=(sd_e2)^2
gen t_test_e2=avg_e2/sqrt(var_e2/n)
drop e2 avg_e2 sd_e2 var_e2 n

* conducting Regressions and Tests for the 5 quintile portfolios
   ↪ created based on the quarterly SIZE of Total Assets (the
   ↪ Hypothesis 3):
drop if atq==. | atq==0
gen log_SIZE=ln(at)
egen SIZE=xtile(log_SIZE), by(yr_qtr) nq(5)
label var SIZE "decile portfolio on Size as natural log of Total
   ↪ Assets"
drop atq log_SIZE yr_qtr
sort SIZE
by SIZE: gen n=_N
reg BHAR AGE GOOD BAD GOODxAGE BADxAGE if SIZE==1, robust
rvfplot
estat vce
preserve
keep if SIZE==1
predict e3a, residual
egen avg_e3a=mean(e3a)
egen sd_e3a=sd(e3a)
gen var_e3a=(sd_e3a)^2
gen t_test_e3a=avg_e3a/sqrt(var_e3a/n)
display t_test_e3a
restore
reg BHAR AGE GOOD BAD GOODxAGE BADxAGE if SIZE==2, robust
rvfplot
estat vce
preserve
keep if SIZE==2
```

```
predict e3b, residual
egen avg_e3b=mean(e3b)
egen sd_e3b=sd(e3b)
gen var_e3b=(sd_e3b)^2
gen t_test_e3b=avg_e3b/sqrt(var_e3b/n)
display t_test_e3b
restore
reg BHAR AGE GOOD BAD GOODxAGE BADxAGE if SIZE==3, robust
rvfplot
estat vce
preserve
keep if SIZE==3
predict e3c, residual
egen avg_e3c=mean(e3c)
egen sd_e3c=sd(e3c)
gen var_e3c=(sd_e3c)^2
gen t_test_e3c=avg_e3c/sqrt(var_e3c/n)
display t_test_e3c
restore
reg BHAR AGE GOOD BAD GOODxAGE BADxAGE if SIZE==4, robust
rvfplot
estat vce
preserve
keep if SIZE==4
predict e3d, residual
egen avg_e3d=mean(e3d)
egen sd_e3d=sd(e3d)
gen var_e3d=(sd_e3d)^2
gen t_test_e3d=avg_e3d/sqrt(var_e3d/n)
display t_test_e3d
restore
reg BHAR AGE GOOD BAD GOODxAGE BADxAGE if SIZE==5, robust
rvfplot
```

```
estat vce
preserve
keep if SIZE==5
predict e3e, residual
egen avg_e3e=mean(e3e)
egen sd_e3e=sd(e3e)
gen var_e3e=(sd_e3e)^2
gen t_test_e3e=avg_e3e/sqrt(var_e3e/n)
display t_test_e3e

****************************

* MERGING DATASETS FOR THE BSI ANALYSIS:

*** merging the CRSP, COMPUSTAT & I/B/E/S datasets ***
* extracting variables essential for calculating Firm Age from CRSP:
use CRSP_1990-2012, clear
drop date prc retx m_capq
sort cusip yr_qtr
by cusip yr_qtr: keep if _n==1

* extracting the date of firm's First Appearance on the Common Stock
   ↪ Market (in case of a missing IPO Date in COMPUSTAT, the date of
   ↪  First Appearance in the CRSP Register is applied; if both are
   ↪ available, the earlier is chosen):
merge 1:1 cusip yr_qtr using COMPUSTATqtr_1990-2010
drop _merge comnam conm atq id
format ipodate %td
replace date_first=ipodate if ipodate<date_first & ipodate!=.
drop if date_first==.
drop ipodate

* merging with I/B/E/S & trimming data for the examined period:
```

```
merge m:1 cusip yr_qtr using IBES_1990-2012, keep (match)
drop id _merge cname surprise_value GOOD BAD
drop if anndats_act<td(1,1,1991) | anndats_act>=td(1,1,1997)

* dropping the observations that coincide with the M&A Activity and
   ↪ the Stock Repurchases:
replace aqaq=0 if aqaq==.
replace prstkccy=0 if prstkccy==.
drop if aqaq!=0 | prstkccy!=0
drop aqaq prstkccy

* generating the Firm Age variable:
gen yearborn=yofd(date_first)
gen yeardata=yofd(fpedats)
gen firm_age=yeardata-yearborn
label var firm_age "Company Age since the First Record in Common
   ↪ Stock Databases"
drop yearborn yeardata date_first
save merged_C+C+I_BSI_step1, replace

*** adjusting I/B/E/S Earnings Announcement dates ***
* coinciding Earnings Announcement & Forecast Period End dates of the
   ↪  examined observations from I/B/E/S with the trading dates
   ↪ according to the Business Calendar created from the CRSP
   ↪ dataset (in case an Earnings Announcement occurs during a non-
   ↪ business day, in order to maintain the Event Window ending 1
   ↪ trading day after the Earnings Announcement date, it is
   ↪ converted to the first available business day preceding that
   ↪ date; in case the Forecast Period End occurs during a non-
   ↪ business day, in order to maintain the Event Window starting 12
   ↪  trading days before the Forecast Period End, it is converted
   ↪ to the first available business day following that date):
use merged_C+C+I_BSI_step1, clear
```

```
gen ann_trd_date = bofd("crsp", anndats_act)
forvalues i = 1/2 {
replace anndats_act=anndats_act-1 if ann_trd_date==.
drop ann_trd_date
gen ann_trd_date = bofd("crsp", anndats_act)
}
assert ann_trd_date!=. if anndats_act!=.
format ann_trd_date %tbcrsp
gen fpe_trd_date = bofd("crsp", fpedats)
forvalues i = 1/3 {
replace fpedats=fpedats+1 if fpe_trd_date==.
drop fpe_trd_date
gen fpe_trd_date = bofd("crsp", fpedats)
}
assert fpe_trd_date!=. if fpedats!=.
format fpe_trd_date %tbcrsp

* creating a variable essential for further merging:
sort cusip anndats_act
by cusip: gen set=_n
save merged_C+C+I_BSI_step2, replace

*** operations essential to obtain a sufficient trading-day margin around Earnings Announcements ***
use merged_C+C+I_BSI_step2, clear
keep cusip anndats_act
sort cusip anndats_act
by cusip: gen anncount=_N
by cusip: keep if _n==1
drop anndats_act
save anncount_BSI, replace

****************************
```

```
* CALCULATING BSI FOR CLIENTS OF A LARGE DISCOUNT BROKERAGE HOUSE:

*** merging the Earnings Announcement data with the Discount
    ↪ Brokerage datasets ***
* formatting the Discount Brokerage BASE dataset:
use base, clear
tostring Household_Open_Date, replace
gen accnt_opndat = date(Household_Open_Date, "19YMD")
format accnt_opndat %td
label var accnt_opndat "Account Opening Date"
keep Account_Number Account_Registration accnt_opndat

* controlling for multiple Account Opening Dates associated with a
    ↪ single Account Number & preserving the observations belonging
    ↪ to the Accounts opened most recently in case of duplicates:
gsort Account_Number -accnt_opndat
quietly by Account_Number: gen dup=cond(_N==1,0,_n)
drop if dup>1
drop dup

* merging the Discount Brokerage BASE dataset with the Discount
    ↪ Brokerage dataset containing TRADES and file formatting:
merge 1:m Account_Number using trades, keep (match)
drop _merge
rename Cusip cusip
tostring Trade_Date, replace
gen date = date(Trade_Date, "19YMD")
format date %td

* generating the variable Cumulative Number of Trades that starts
    ↪ with 1 on the earliest Trade Date associated with an Account
    ↪ and increases by 1 with every subsequent Trade (as the dataset
```

```
    ↪ contains only the transactions made during the years 1991-1996,
    ↪  this variable is only relevant in case of the Accounts opened
    ↪ since 1991):
sort Account_Number date
by Account_Number: gen cumul_trds=_n
label var cumul_trds "Cumulative Number of Trades"

* preserving the trades only related to the Common Stock & performing
    ↪  operations essential to obtain a sufficient trading-day margin
    ↪  around the Earnings Announcements:
merge m:1 cusip using anncount_BSI, keep (match)
keep if Product_Code=="COM"
keep Account_Number Account_Registration accnt_opndat Buy_Sell
    ↪ Quantity cusip date cumul_trds anncount
sort cusip
expand anncount
drop anncount
sort cusip date
by cusip date: gen set=_n

* merging TRADES with the Earnings Announcement data:
merge m:1 cusip set using merged_C+C+I_BSI_step2, keep (match)
drop _merge

* coinciding the Trade Dates with the Trading Dates according to the
    ↪ Business Calendar created from the CRSP dataset (in case a
    ↪ Trade Date occurs during a non-business day, it is converted to
    ↪  the first available business day following that date, as
    ↪ trades can be executed only during business dates):
gen trd_date = bofd("crsp", date)
replace date=date+1 if trd_date==.
drop trd_date
gen trd_date = bofd("crsp", date)
```

```
assert trd_date!=. if date!=.
format trd_date %tbcrsp

* reducing the trades surrounding the examined Earnings Announcement
    ↪ only to the dates matching the ‘‘postret’’ interval:
drop if trd_dat<fpe_trd_date-12 | trd_dat>ann_trd_date+1

* assigning ID to each Earnings Announcement observation:
sort cusip set
egen group_id = group(cusip set)
drop set fpedats anndats_act ann_trd_date fpe_trd_date trd_dat
save TRADES_postret, replace

* generating subportfolios based on the Firm Age for the ‘‘postret’’
    ↪ interval:
use TRADES_postret, clear
tostring firm_age, replace
replace firm_age="6-10" if firm_age=="6" | firm_age=="7" | firm_age
    ↪ =="8" | firm_age=="9" | firm_age=="10"
replace firm_age="11-15" if firm_age=="11" | firm_age=="12" |
    ↪ firm_age=="13" | firm_age=="14" | firm_age=="15"
replace firm_age="16-20" if firm_age=="16" | firm_age=="17" |
    ↪ firm_age=="18" | firm_age=="19" | firm_age=="20"
replace firm_age=">20" if firm_age!="0" & firm_age!="1" & firm_age
    ↪ !="2" & firm_age!="3" & firm_age!="4" & firm_age!="5" &
    ↪ firm_age!="6-10" & firm_age!="11-15" & firm_age!="16-20"
save TRADES_postret_brackets, replace

*** calculating BSI from the Discount Brokerage dataset ***
* calculating BSI for a company ’i’ based on the number of Buys and
    ↪ on the number of Sells:
use TRADES_postret_brackets, clear
drop if SURP==0
```

```
sort Account_Registration group_id Buy_Sell
by Account_Registration group_id Buy_Sell: gen sum=_N
by Account_Registration group_id: gen BUY=sum if Buy_Sell=="B"
by Account_Registration group_id: egen sum_BUY=max(BUY)
replace sum_BUY=0 if sum_BUY==.
by Account_Registration group_id: gen SELL=sum if Buy_Sell=="S"
by Account_Registration group_id: egen sum_SELL=min(SELL)
replace sum_SELL=0 if sum_SELL==.
gen BSI_i=(sum_BUY-sum_SELL)/(sum_BUY+sum_SELL)
drop BUY SELL sum Buy_Sell Quantity sum_BUY sum_SELL
by Account_Registration group_id: keep if _n==1
sort Account_Registration firm_age SURPRISE
by Account_Registration firm_age SURPRISE: egen BSI=mean(BSI_i)
by Account_Registration firm_age SURPRISE: gen n=_N
by Account_Registration firm_age SURPRISE: egen sd_BSI=sd(BSI_i)
keep Account_Registration SURPRISE firm_age BSI n sd_BSI
gen BSIpos=BSI if SURPRISE==1
gen npos=n if SURPRISE==1
gen varBSIpos=(sd_BSI)^2 if SURPRISE==1
gen BSIneg=BSI if SURPRISE==-1
gen nneg=n if SURPRISE==-1
gen varBSIneg=(sd_BSI)^2 if SURPRISE==-1
by Account_Registration firm_age: egen BSI_pos=max(BSIpos)
by Account_Registration firm_age: egen n_pos=max(npos)
by Account_Registration firm_age: egen varBSI_pos=max(varBSIpos)
by Account_Registration firm_age: egen BSI_neg=max(BSIneg)
by Account_Registration firm_age: egen n_neg=max(nneg)
by Account_Registration firm_age: egen varBSI_neg=max(varBSIneg)
by Account_Registration firm_age: keep if _n==1
gen BSI_diff=BSI_pos-BSI_neg
gen t_test=BSI_diff/sqrt((varBSI_pos/n_pos)+(varBSI_neg/n_neg))
keep Account_Registration firm_age BSI_pos n_pos BSI_neg n_neg
    ↪ BSI_diff t_test
```

```
export excel using "BSI_brokerage", firstrow(variables)

* calculating VOLUME BSI for a company 'i' based on the volume of
   ↪ Buys and on the volume of Sells:
use TRADES_postret_brackets, clear
drop if SURP==0
sort Account_Registration group_id Buy_Sell
by Account_Registration group_id Buy_Sell: egen sum=sum(Quantity)
by Account_Registration group_id: gen BUY=sum if Buy_Sell=="B"
by Account_Registration group_id: egen sum_BUY=max(BUY)
replace sum_BUY=0 if sum_BUY==.
by Account_Registration group_id: gen SELL=sum if Buy_Sell=="S"
by Account_Registration group_id: egen sum_SELL=min(SELL)
replace sum_SELL=0 if sum_SELL==.
gen abs_sum_SELL=abs(sum_SELL)
by Account_Registration group_id: gen BSI_i=(sum_BUY-abs_sum_SELL)/(
   ↪ sum_BUY+abs_sum_SELL)
drop BUY SELL sum Buy_Sell Quantity sum_BUY sum_SELL abs_sum_SELL
by Account_Registration group_id: keep if _n==1
sort Account_Registration firm_age SURPRISE
by Account_Registration firm_age SURPRISE: egen BSI=mean(BSI_i)
by Account_Registration firm_age SURPRISE: gen n=_N
by Account_Registration firm_age SURPRISE: egen sd_BSI=sd(BSI_i)
keep Account_Registration SURPRISE firm_age BSI n sd_BSI
gen BSIpos=BSI if SURPRISE==1
gen npos=n if SURPRISE==1
gen varBSIpos=(sd_BSI)^2 if SURPRISE==1
gen BSIneg=BSI if SURPRISE==-1
gen nneg=n if SURPRISE==-1
gen varBSIneg=(sd_BSI)^2 if SURPRISE==-1
by Account_Registration firm_age: egen BSI_pos=max(BSIpos)
by Account_Registration firm_age: egen n_pos=max(npos)
by Account_Registration firm_age: egen varBSI_pos=max(varBSIpos)
```

```
by Account_Registration firm_age: egen BSI_neg=max(BSIneg)
by Account_Registration firm_age: egen n_neg=max(nneg)
by Account_Registration firm_age: egen varBSI_neg=max(varBSIneg)
by Account_Registration firm_age: keep if _n==1
gen BSI_diff=BSI_pos-BSI_neg
gen t_test=BSI_diff/sqrt((varBSI_pos/n_pos)+(varBSI_neg/n_neg))
keep Account_Registration firm_age BSI_pos n_pos BSI_neg n_neg
   ↪ BSI_diff t_test
export excel using "VOL_BSI_brokerage", firstrow(variables)

*** calculating BSI from the Discount Brokerage dataset for the
   ↪ portfolios based on the Cumulative Number of Trades
* calculating BSI for the portfolios based on the Cumulative Number
   ↪ of Trades:
use TRADES_postret_brackets, clear
drop if Account_Registration!="IN"
drop if accnt_opndat<td(1,1,1991)
drop Account_Registration accnt_opndat
gen cumul_n_trds="1-50" if cumul_trds<=50
replace cumul_n_trds="51-100" if 50<cumul_trds & cumul_trds<=100
replace cumul_n_trds="100+" if 100<cumul_trds
drop if SURP==0
sort cumul_n_trds group_id Buy_Sell
by cumul_n_trds group_id Buy_Sell: gen sum=_N
by cumul_n_trds group_id: gen BUY=sum if Buy_Sell=="B"
by cumul_n_trds group_id: egen sum_BUY=max(BUY)
replace sum_BUY=0 if sum_BUY==.
by cumul_n_trds group_id: gen SELL=sum if Buy_Sell=="S"
by cumul_n_trds group_id: egen sum_SELL=min(SELL)
replace sum_SELL=0 if sum_SELL==.
gen BSI_i=(sum_BUY-sum_SELL)/(sum_BUY+sum_SELL)
drop BUY SELL sum Buy_Sell Quantity sum_BUY sum_SELL
by cumul_n_trds group_id: keep if _n==1
```

```
sort cumul_n_trds firm_age SURPRISE
by cumul_n_trds firm_age SURPRISE: egen BSI=mean(BSI_i)
by cumul_n_trds firm_age SURPRISE: gen n=_N
by cumul_n_trds firm_age SURPRISE: egen sd_BSI=sd(BSI_i)
keep cumul_n_trds SURPRISE firm_age BSI n sd_BSI
gen BSIpos=BSI if SURPRISE==1
gen npos=n if SURPRISE==1
gen varBSIpos=(sd_BSI)^2 if SURPRISE==1
gen BSIneg=BSI if SURPRISE==-1
gen nneg=n if SURPRISE==-1
gen varBSIneg=(sd_BSI)^2 if SURPRISE==-1
by cumul_n_trds firm_age: egen BSI_pos=max(BSIpos)
by cumul_n_trds firm_age: egen n_pos=max(npos)
by cumul_n_trds firm_age: egen varBSI_pos=max(varBSIpos)
by cumul_n_trds firm_age: egen BSI_neg=max(BSIneg)
by cumul_n_trds firm_age: egen n_neg=max(nneg)
by cumul_n_trds firm_age: egen varBSI_neg=max(varBSIneg)
by cumul_n_trds firm_age: keep if _n==1
gen BSI_diff=BSI_pos-BSI_neg
gen t_test=BSI_diff/sqrt((varBSI_pos/n_pos)+(varBSI_neg/n_neg))
keep cumul_n_trds firm_age BSI_pos n_pos BSI_neg n_neg BSI_diff
   ↪ t_test
export excel using "BSI_brok_cumul", firstrow(variables)

* calculating VOLUME BSI for the portfolios based on the Cumulative
   ↪ Number of Trades:
use TRADES_postret_brackets, clear
drop if Account_Registration!="IN"
drop if accnt_opndat<td(1,1,1991)
drop Account_Registration accnt_opndat
gen cumul_n_trds="1-50" if cumul_trds<=50
replace cumul_n_trds="51-100" if 50<cumul_trds & cumul_trds<=100
replace cumul_n_trds="100+" if 100<cumul_trds
```

```
drop if SURP==0
sort cumul_n_trds group_id Buy_Sell
by cumul_n_trds group_id Buy_Sell: egen sum=sum(Quantity)
by cumul_n_trds group_id: gen BUY=sum if Buy_Sell=="B"
by cumul_n_trds group_id: egen sum_BUY=max(BUY)
replace sum_BUY=0 if sum_BUY==.
by cumul_n_trds group_id: gen SELL=sum if Buy_Sell=="S"
by cumul_n_trds group_id: egen sum_SELL=min(SELL)
replace sum_SELL=0 if sum_SELL==.
gen abs_sum_SELL=abs(sum_SELL)
by cumul_n_trds group_id: gen BSI_i=(sum_BUY-abs_sum_SELL)/(sum_BUY+
    ↪ abs_sum_SELL)
drop BUY SELL sum Buy_Sell Quantity sum_BUY sum_SELL abs_sum_SELL
by cumul_n_trds group_id: keep if _n==1
sort cumul_n_trds firm_age SURPRISE
by cumul_n_trds firm_age SURPRISE: egen BSI=mean(BSI_i)
by cumul_n_trds firm_age SURPRISE: gen n=_N
by cumul_n_trds firm_age SURPRISE: egen sd_BSI=sd(BSI_i)
keep cumul_n_trds SURPRISE firm_age BSI n sd_BSI
gen BSIpos=BSI if SURPRISE==1
gen npos=n if SURPRISE==1
gen varBSIpos=(sd_BSI)^2 if SURPRISE==1
gen BSIneg=BSI if SURPRISE==-1
gen nneg=n if SURPRISE==-1
gen varBSIneg=(sd_BSI)^2 if SURPRISE==-1
by cumul_n_trds firm_age: egen BSI_pos=max(BSIpos)
by cumul_n_trds firm_age: egen n_pos=max(npos)
by cumul_n_trds firm_age: egen varBSI_pos=max(varBSIpos)
by cumul_n_trds firm_age: egen BSI_neg=max(BSIneg)
by cumul_n_trds firm_age: egen n_neg=max(nneg)
by cumul_n_trds firm_age: egen varBSI_neg=max(varBSIneg)
by cumul_n_trds firm_age: keep if _n==1
gen BSI_diff=BSI_pos-BSI_neg
```

```
gen t_test=BSI_diff/sqrt((varBSI_pos/n_pos)+(varBSI_neg/n_neg))
keep cumul_n_trds firm_age BSI_pos n_pos BSI_neg n_neg BSI_diff
   ↪ t_test
export excel using "VOL_BSI_brok_cumul", firstrow(variables)

****************************

* CALCULATING BSI FOR LARGE COMPANIES BASED ON THE CHANGE IN HOLDINGS
   ↪  REPORTED IN 13F FILINGS:
* formatting the dataset with Changes in 13F Filings:
use 13F_CHANGE, clear
drop mgrno
gen yr_qtr = qofd(fdate)
format yr_qtr %tq
label var yr_qtr "Year & Quarter subject to report"
gen Buy_Sell="B" if change>0
replace Buy_Sell="S" if change<0
save 13F_CHANGE_adj, replace

* controlling for multiple Earnings Announcements occurring in the
   ↪ same Calendar Quarter in a single Company & preserving the
   ↪ observation belonging to the latest Earnings Announcement in
   ↪ case of duplicates (as 13F Filings are submitted at the end of
   ↪ the Calendar Quarter, the latest Earnings Announcement of the
   ↪ same Quarter is expected to exert the highest impact on the
   ↪ company holdings):
use merged_C+C+I_BSI_step1, clear
drop yr_qtr
gen yr_qtr = qofd(anndats_act)
format yr_qtr %tq
label var yr_qtr "Year & Quarter of Earnings Announcement"
gsort cusip yr_qtr -anndats_act
by cusip yr_qtr: gen dup=cond(_N==1,0,_n)
```

```
drop if dup>1
drop dup

* merging the Earnings Announcement data with the dataset containing
   ↪ Changes in 13F Filings:
merge 1:m cusip yr_qtr using 13F_CHANGE_adj, keep (match)
drop fdate _merge

* labeling Institutional categories:
tostring type, replace
replace type="Banks" if type=="1"
replace type="Insurance Companies" if type=="2"
replace type="Investment Companies" if type=="3"
replace type="Investment Advisors" if type=="4"
replace type="Other Institutional Investors" if type=="5"
label var type "Institutional Investor Type"

* generating subportfolios based on the Firm Age:
tostring firm_age, replace
replace firm_age="6-10" if firm_age=="6" | firm_age=="7" | firm_age
   ↪ =="8" | firm_age=="9" | firm_age=="10"
replace firm_age="11-15" if firm_age=="11" | firm_age=="12" |
   ↪ firm_age=="13" | firm_age=="14" | firm_age=="15"
replace firm_age="16-20" if firm_age=="16" | firm_age=="17" |
   ↪ firm_age=="18" | firm_age=="19" | firm_age=="20"
replace firm_age=">20" if firm_age!="0" & firm_age!="1" & firm_age
   ↪ !="2" & firm_age!="3" & firm_age!="4" & firm_age!="5" &
   ↪ firm_age!="6-10" & firm_age!="11-15" & firm_age!="16-20"
save 13F_type, replace

* calculating VOLUME BSI for All Institutions:
use 13F_type, clear
sort cusip yr_qtr Buy_Sell
```

```
by cusip yr_qtr Buy_Sell: egen sum=sum(change)
by cusip yr_qtr: gen BUY=sum if Buy_Sell=="B"
by cusip yr_qtr: egen sum_BUY=max(BUY)
replace sum_BUY=0 if sum_BUY==.
by cusip yr_qtr: gen SELL=sum if Buy_Sell=="S"
by cusip yr_qtr: egen sum_SELL=min(SELL)
replace sum_SELL=0 if sum_SELL==.
gen abs_sum_SELL=abs(sum_SELL)
by cusip yr_qtr: gen BSI_i=(sum_BUY-abs_sum_SELL)/(sum_BUY+
   ↪ abs_sum_SELL)
drop BUY SELL sum Buy_Sell change sum_BUY sum_SELL abs_sum_SELL
by cusip yr_qtr: keep if _n==1
drop if SURP==0
sort firm_age SURPRISE
by firm_age SURPRISE: egen BSI=mean(BSI_i)
by firm_age SURPRISE: gen n=_N
by firm_age SURPRISE: egen sd_BSI=sd(BSI_i)
keep SURPRISE type firm_age BSI n sd_BSI
gen BSIpos=BSI if SURPRISE==1
gen npos=n if SURPRISE==1
gen varBSIpos=(sd_BSI)^2 if SURPRISE==1
gen BSIneg=BSI if SURPRISE==-1
gen nneg=n if SURPRISE==-1
gen varBSIneg=(sd_BSI)^2 if SURPRISE==-1
by firm_age: egen BSI_pos=max(BSIpos)
by firm_age: egen n_pos=max(npos)
by firm_age: egen varBSI_pos=max(varBSIpos)
by firm_age: egen BSI_neg=max(BSIneg)
by firm_age: egen n_neg=max(nneg)
by firm_age: egen varBSI_neg=max(varBSIneg)
by firm_age: keep if _n==1
gen BSI_diff=BSI_pos-BSI_neg
gen t_test=BSI_diff/sqrt((varBSI_pos/n_pos)+(varBSI_neg/n_neg))
```

```
keep firm_age BSI_pos n_pos BSI_neg n_neg BSI_diff t_test
export excel using "VOL_BSI_13F", firstrow(variables)

* calculating VOLUME BSI by the Institutional Investor category:
use 13F_type, clear
sort type cusip yr_qtr Buy_Sell
by type cusip yr_qtr Buy_Sell: egen sum=sum(change)
by type cusip yr_qtr: gen BUY=sum if Buy_Sell=="B"
by type cusip yr_qtr: egen sum_BUY=max(BUY)
replace sum_BUY=0 if sum_BUY==.
by type cusip yr_qtr: gen SELL=sum if Buy_Sell=="S"
by type cusip yr_qtr: egen sum_SELL=min(SELL)
replace sum_SELL=0 if sum_SELL==.
gen abs_sum_SELL=abs(sum_SELL)
by type cusip yr_qtr: gen BSI_i=(sum_BUY-abs_sum_SELL)/(sum_BUY+
   ↪ abs_sum_SELL)
drop BUY SELL sum Buy_Sell change sum_BUY sum_SELL abs_sum_SELL
by type cusip yr_qtr: keep if _n==1
drop if SURP==0
sort type firm_age SURPRISE
by type firm_age SURPRISE: egen BSI=mean(BSI_i)
by type firm_age SURPRISE: gen n=_N
by type firm_age SURPRISE: egen sd_BSI=sd(BSI_i)
keep SURPRISE type firm_age BSI n sd_BSI
gen BSIpos=BSI if SURPRISE==1
gen npos=n if SURPRISE==1
gen varBSIpos=(sd_BSI)^2 if SURPRISE==1
gen BSIneg=BSI if SURPRISE==-1
gen nneg=n if SURPRISE==-1
gen varBSIneg=(sd_BSI)^2 if SURPRISE==-1
by type firm_age: egen BSI_pos=max(BSIpos)
by type firm_age: egen n_pos=max(npos)
by type firm_age: egen varBSI_pos=max(varBSIpos)
```

```
by type firm_age: egen BSI_neg=max(BSIneg)
by type firm_age: egen n_neg=max(nneg)
by type firm_age: egen varBSI_neg=max(varBSIneg)
by type firm_age: keep if _n==1
gen BSI_diff=BSI_pos-BSI_neg
gen t_test=BSI_diff/sqrt((varBSI_pos/n_pos)+(varBSI_neg/n_neg))
keep type firm_age BSI_pos n_pos BSI_neg n_neg BSI_diff t_test
export excel using "VOL_BSI_13F_type", firstrow(variables)
```

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