An empirical analysis of behavioral finance theories in international equity markets

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Kurzfassung

Finanzmärkte spielen eine zentrale Rolle in modernen Volkswirtschaften und sind daher Gegenstand unzähliger theoretischer und empirischer Untersuchungen. Dennoch können die bisherigen Ansätze im Rahmen des neoklassischen, rationalen Theoriegebäudes das Geschehen auf Finanzmärkten weder erklären noch prognostizieren. Daher wurden in der jüngeren Vergangenheit neue Theorien im Feld "Behavioral Finance" entwickelt, die zum Ziel haben, das Verhalten von Investoren auf Finanzmärkten realistischer zu modellieren und vom Ideal eines vollkommen rationalen Investors - angesichts psychologischer und informatorischer Beschränkungen - abzurücken.

Die fünf Kapitel dieser Dissertation beinhalten empirische Tests von grundlegenden Erkenntnissen der Behavioral Finance und untersuchen, ob die Annahme irrationaler oder beschränkt rationaler Investoren sinnvoll ist, um Finanzmarktprozesse und das beobachtete Verhalten von Investoren zu verstehen.

Hinsichtlich der Ergebnisse können zwei zentrale Schlussfolgerungen gezogen werden. Erstens wird gezeigt, dass nicht-rationale Entscheidungsprozesse einen signifikanten Einfluss auf Finanzmarktbewegungen und Investorenverhalten ausüben. Dieses Ergebnis zieht sich durch alle fünf Kapitel der Arbeit und zeigt sich in der Prognosekraft von Investorenstimmungen für zukünftige, langfristige Renditen, der empirischen Erklärungskraft von Kurzfristorientierung und Verlustaversion für das Verhalten von erwarteten Querschnittsrenditen und den systematischen Verzerrungen im Anlageverhalten von institutionellen Investoren und Privatanlegern.

Eine zweite Schlussfolgerung betrifft die Rolle von institutionellen und privaten Anlegern. Wie die empirischen Ergebnisse dieser Arbeit zeigen, verhalten sich diese beiden Gruppen von Marktteilnehmern signifikant unterschiedlich. Während institutionelle Anleger dem Ideal des rationalen Investors deutlich näher kommen, unterliegen private Anleger stärker systematisch verzerrtem Verhalten und stellen durch ihr Verhalten tendenziell ein Hindernis für effiziente Märkte dar.

Schlagwörter: Vermögenspreise, Behavioral Finance, Erwartete Renditen, Verlustaversion

Abstract

Financial markets play a key role in modern economies and are thus subject to a huge amount of theoretical and empirical research. Yet there is little evidence that standard neoclassical, rational models explain determinants of financial market movements, let alone forecast these movements. Therefore, new theories have been put forward under the roof of "behavioral finance" that aim at a better description of real-world behavior of investors who do not confine to the ideal of the rational decision-maker due to psychological and information-processing constraints.

The five chapters of this dissertation empirically test several key concepts of behavioral finance and investigate, whether the hypothesis of non-rational decision making is helpful for understanding the behavior of financial market movements and the behavior of investors.

Summarizing the evidence, two major conclusions can be drawn from the empirical results presented here. First, it is found that behavioral biases matter for asset prices and investment behavior. This conclusion is rooted in all five chapters and manifests itself through the predictive power of investor sentiment for expected long-horizon returns, the empirical success of myopic loss aversion for explaining the cross-section of expected stock returns and the systematic portfolio biases of laymen and professionals.

A second conclusion can be drawn for the role of institutional versus individual investors. As the results document, there is a significant difference between the two investor groups. Whereas institutions seem to be more in line with the ideal of rational investors who collect and aggregate fundamental information, individuals are more heavily plagued by systematic biases in their investment behavior and seem to represent a source of noise trader risk in financial markets.

Keywords: Asset Pricing, Behavioral Finance, Expected Returns, Loss Aversion

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Motivation and summary of main results

It has become an almost common exercise in the empirical finance literature to discover "anomalies", "conundrums", and "puzzles", i.e. behavior of investors or behavior of financial prices that is sharply at odds with standard neoclassical theory. Bossaerts (2002, p. x) for example concludes that *"[...], asset pricing is paradoxical. On the one hand, the theory is so persuasive that it is widely believed to be correct, [...]. Yet there is little evidence that the theory explains the past, let alone that it predicts the future."* Since many researchers find it hard to stick to a theoretical framework whose predictions are routinely rejected by empirical findings, new theories have been put forward that aim at a better description of real-world behavior of investors who do not confine to the ideal of the rational decision-maker due to psychological and information-processing constraints.

Specifically, the literature tends to view individual investors as noise traders who base portfolio decisions on non-fundamental or pseudo-information (Black, 1986). Verification or rejection of this hypothesis can have far-reaching implications for the efficiency of financial markets as a whole and also raises a number of normative and positive issues in economics. Regarding possible normative implications, Shleifer (2000) for example points out, that individuals should not be allowed to manage their savings for retirement if it was known that they make irrational portfolio choices. Furthermore, if noise trader sentiment becomes systematic and does not wash out in the aggregate, then it also challenges the efficient market hypotheses since persistent waves of systematic overoptimism or –pessimism by noise traders drive a wedge between fundamental values and market prices which cannot be eliminated by riskless arbitrage (these are the so-called *limits to arbitrage*, see Shleifer and Vishny, 1997). As with the policy issue raised above, this is not just a side-show for behaviorally oriented finance researchers but has serious implications for the real economy and a positive implication. If irrational sentiment drives up (down) prices above (below) fundamentally warranted levels for e.g. some industries of the economy, then these industries have incentives to issue new shares and raise additional capital (e.g. through a channel based on Tobin's *Q*-theory of investment) which leads to a misallocation of resources in the economy. Polk and Sapienza (2006) do indeed find evidence for such a misallocation of capital and conclude that sentiment has real economic consequences so that systematic irrational sentiment is not neutral.

Clearly, the literature has identified several behavioral biases and the above described sentiment phenomenon is just one of several potential departures from rational decision making. The five chapters of this thesis deal with some of the most widely studied behavioral anomalies and their consequences for sources of predictability in financial markets, asset prices and portfolio choices of different types of investors. These five chapters are briefly described in the following paragraphs.

The first chapter “Institutional and individual sentiment: Smart money and noise trader risk” deals with the question whether sentiment matters for asset prices and whether individuals and institutions differ in this respect. The main part of the chapter uses a predictive regression approach to test the hypothesis that individuals are noise traders and that institutions are rational market participants who correctly aggregate fundamental information (so-called “smart money", e.g. Campbell and Kyle, 1993). As noted above, individuals are commonly thought of as being noise traders because of their low sophistication and the fact that they are just too time-constrained to access and process the sheer volume of fundamental information about corporate and economic fundamentals available every day. Due to their low sophistication, individuals are thought of as being subject to several biases in decision making such as e.g. herding, and non-Bayesian updating of prior beliefs. The latter two arguments naturally lead to a simple test of the hypothesis that individuals represent noise traders: If individuals become overly optimistic (pessimistic) about a sequence of good news, then their buying (selling) pressure will drive financial prices above (below) fundamentally warranted levels. This overvaluation can persist for some time since it is risky to arbitrage this misevaluation when sentiment (overoptimism or –pessimism) is persistent.

However, in the long-run, all mispricing will eventually be corrected and prices must return to fundamental values. Therefore, a test of the noise trader hypothesis can be conducted by regressing future returns on current individual sentiment. Theoretically, the noise trader paradigm suggests that the coefficient of sentiment should be negative. Higher optimism (sentiment) leads to an overvaluation today that has to be corrected in the future, i.e. expected returns must be lower in the future holding everything else equal.

Contrary to the individual investors, institutions are commonly thought of as representing the rational part of the market, i.e. fundamentally oriented investors who correctly aggregate and process the relevant information. If this hypothesis is true, a regression of future returns on current institutional sentiment should produce a positive slope coefficient estimate. This result would indicate that institutional expectations are correct on average.

The first chapter tests these two hypotheses and analyzes a range of related topics or robustness issues. The main conclusion is that – at least for the data set of German investors investigated – individuals seem to be noise traders and that institutions seem to be smart money.

The second chapter “Investor sentiment, herd-like behavior and stock returns: Evidence from 18 industrialized countries” builds on the same assumptions and theoretical background as the first chapter but goes one step beyond and conducts an out-of-sample test of the noise trader hypotheses (due to data availability, institutional sentiment is not analyzed). I test whether a proxy for individual sentiment has the expected effect as discussed above on expected returns in 18 industrialized countries around the world, covering among others, the major markets in the U.S., U.K., Japan, or Germany. This out-of-sample test seems useful since most of the earlier work in this area is based exclusively on U.S. data and the resulting evidence might be subject to the usual data-mining problem. It is found that the sentiment-return relation differs a lot between countries and that there is a significant effect of sentiment on returns for only 10 out of 18 countries.

In a second step I investigate possible sources that may explain why there is a strong and significant sentiment effect on returns for some countries but not for others. The results show that those countries tend to have a higher noise trader impact, that have less developed institutions, lower levels of education, and a culturally anchored tendency to show herd behavior and overreaction. Especially the latter finding corroborates empirical evidence by Chui, Titman and Wei (2005) who show that cultural factors might play an important role in explaining market anomalies internationally.

The third chapter "A prospect-theoretical interpretation of momentum returns" deals with a different fundamental behavioral approach, namely loss aversion and myopic behavior. This so-called myopic loss aversion is a cornerstone of modern behavioral finance and models agents as having short planning horizons (myopic behavior) and as being much more sensitive to losses than to gains of the same size, i.e. there is kink in the utility function at a pre-specified reference level. Myopic loss aversion has been employed in several asset pricing studies throughout the years and in various contexts (sees e.g. Benartzi and Thaler, 1995, Barberis and Huang, 2001, Barberis, Santos, and Huang, 2001, or Barberis, Huang, and Thaler, 2006). In this chapter, we apply myopic loss aversion to the puzzling behavior of momentum returns.

Momentum strategies boil down to buying past winning stocks while simultaneously selling (short) past loser stocks. While this strategy is one of the simplest asset allocation rules one might think of, the returns to momentum portfolios are extremely high and largely unexplained by standard risk factors employed in the literature (see e.g. Jegadeesh and Titman, 2001).

Although momentum returns seem to offer a free lunch under a rational asset pricing framework, the chapter shows that there is considerable risk following these strategies when investors have short planning horizons (as is well documented for fund managers and individual investors) and when they are loss averse. Therefore, momentum returns seem to offer an equilibrium compensation for risk under a more realistic utility specification (and no riskless excess returns).

The fourth chapter "Myopic loss aversion and the cross-section of U.S. stock returns: Empirical evidence" extends the third chapter in two dimensions. First, the sample of test assets is expanded from just looking at momentum returns to a large set of 115 investment styles (e.g. value versus growth stocks, small vs. large stocks, industry portfolios). This seems to be an important test given recent critical comments in the academic literature (Cochrane, 2006, Lewellen, Shanken, and Nagel, 2006) who complain about the fact that ostensibly successful asset pricing models often work for specific samples of test assets only (e.g. only for small versus large stocks but not for industry portfolios). Second, the chapter explicitly tests whether a risk factor constructed from the myopic loss aversion framework is priced cross-sectionally when including other prominent risk factors from the earlier literature.

It is found that myopic loss aversion seems relatively successful in capturing the risk of different investment strategies and that the risk factor constructed from the myopic loss aversion framework is dominant relative to other risk factors employed in the literature.

Finally, the fifth chapter "Does professionalism consistently affect portfolio biases" deals with the question whether behavioral biases (as e.g. documented in the first four chapters) may be overcome by professionalism of market participants. Contrary to economic intuition, professionalism does not seem to uniformly lead to more rational behavior and the existing literature does not paint a clear picture on this point. While e.g. Haigh and List (2005) or Dasgupta et al. (2006) show that professionals may perform even worse than laymen, there are other studies showing that professionalism may be a performance enhancing factor (e.g. List, 2003, Locke and Mann, 2005, Alevy et al., 2007). Therefore, we conduct a survey study of about 500 investors covering institutional investors, investment advisors and individual investors to investigate whether different dimensions of professional behavior drive out behavioral biases (such as home bias, high turnover and the disposition effect) or not.

The survey approach is helpful here, since it allows investigation of unconstrained behavior. Especially institutional investors are often constrained in their portfolio choice due to legal restrictions or restrictions and incentives of their employer, so that actual trading data must be polluted by these influences. Therefore, we rely on a survey approach that does not impose restrictions on the participants and which provides new insights into the behavior of the three types of investors.

It is found that three different dimensions of professionalism (occupation, experience, and "market knowledge") are uniformly beneficial for investment behavior and reduce portfolio biases. The estimated effects are statistically significant, economically large and robust to different regression specifications.

Summarizing the evidence, two major conclusions can be drawn. First, it is found that behavioral biases matter for asset prices and investment behavior. This conclusion is rooted in all five chapters and manifests itself through the predictive power of sentiment (chapters 1 and 2), the empirical success of myopic loss aversion for asset pricing (chapters 3 and 4) and the portfolio biases documented in chapter 5. Especially chapter 4 shows that incorporating observed real-world elements into agents' utility function, drastically increases the performance of asset pricing models for a variety of test assets.

A second conclusion can be drawn for the role of institutional versus individual investors. Both chapter 1 and chapter 5 show that there is a significant difference between the two investor groups. Whereas chapter 1 shows that institutions seem to be rational investors who collect and aggregate fundamental information, chapter 5 shows that institutions do indeed show significantly less biased behavior than individuals. As discussed in the beginning of this motivation, these findings contrast sharply with the findings for individuals and may have far-reaching implications for the real economy and for the design of retirement security systems.

Chapter 1: Institutional and individual sentiment: Smart money and noise trader risk?[*]

1.1 Introduction

This chapter empirically investigates two questions that have been subject to a large amount of research effort and debate in financial economics, namely (i) does investor sentiment matter for stock returns, and (ii) what is the difference between individual and institutional investors in financial markets?

While it seems to be generally accepted that institutions differ from individuals due to their size and sophistication (Kaniel, Saar and Titman, 2005) there is considerable disagreement in how these two investor groups differ from each other and how this difference affects market processes like price formation and liquidity provision. Several studies find institutions to be informed investors or "smart money"[1] (e.g. Chakravarty, 2001, Jones and Lipson, 2004, Sias, Starks and Titman, 2006) and individual investors to be irrational noise traders or "dumb money" (Frazzini and Lamont, 2005, Bange, 2000). However, this evidence is accompanied by the finding that institutions deliberately herd in and out of stocks (see e.g. Nofsinger and Sias, 1999, Sias, 2004) and that they heavily rely on momentum-style strategies (Badrinath and Wahal, 2002, Griffin, Harris and Topaloglu, 2003). Furthermore, "dumb" individuals seem to earn excess returns by providing immediacy for institutional trading demands at high frequencies (Kaniel, Saar and Titman, 2005, Campbell, Ramadorai and Voulteenaho, 2005). Therefore, the evidence from real-world trading data so far is not conclusive regarding the role of these two investor groups.

The question whether sentiment, or the mood and expectations of investors, matter for stock returns is more controversial and supporters from the behavioral

[*]This chapter is based on a paper published in the International Journal of Forecasting 23, p. 127-145 (2007), used with permission from Elsevier.

[1]We refer to institutions as smart money in the sense of informed investors (e.g. Campbell and Kyle, 1993) and not in the narrower context of mutual fund flows only as in Zheng (1999).

side (e.g. Shiller, 2003) and critics from the rational camp (e.g. Fama, 1998) have arguments in favor of this view or against it. While theoretical models have early incorporated the existence of noise traders into equilibrium asset pricing (Kyle, 1985, DeLong et al., 1990), empirical evidence on the relevance of investor sentiment does not provide clear findings (see e.g. the polar results in Brown and Cliff, 2005 and Wang, Keswani and Taylor, 2006).

We affiliate these two questions and investigate whether sentiment of institutional investors and individuals matters for aggregate stock market movements and whether the influence of sentiment of these two groups is systematically different. Using a new data set that covers both institutional and individual investors we find, first, that sentiment matters for several stock markets around the world and over intermediate horizons of up to one year and a half. Second, there is a sharp difference between the two investor groups. Institutional investor sentiment forecasts stock returns correctly on average. Individual sentiment negatively predicts market movements in a way that is consistent with the hypothesis that overoptimistic (-pessimistic) noise traders drive markets away from intrinsic values. This overoptimism or -pessimism has to be corrected eventually so that prices return to their intrinsic values over intermediate to long horizons which gives rise to the negative relation between individual sentiment and expected stock returns (see e.g. Brown and Cliff, 2005 or Lemmon and Portniaguina, 2006). Third, in line with these findings, institutional investors become more pessimistic (optimistic) when they expect individuals to be more optimistic (pessimistic) since they recognize that prices might have been driven above (below) fundamental values. Also, institutional investors become more optimistic (pessimistic) when they expect individuals to become even more (less) optimistic (pessimistic) since they recognize that noise traders might push prices even higher above (further below) fundamental values as discussed in the behavioral finance literature (see Shleifer, 2000).

Therefore, our contribution to the literature is twofold. We first employ a new data set that covers genuine investor sentiment from a weekly survey, twice-separated on individual and institutional investors as well as on short and medium forecasting horizons based upon several major stock markets around the world. This data set allows us to analyze investor sentiment while controlling for factors such as the geographical location of a market, forecast horizon and sophistication of investors.

This is new to the literature since previous studies have to rely on proxies for (mostly institutional) sentiment (e.g. Neal and Wheatley, 1998 or Bodurtha, Kim and Lee, 1995), experimental data (DeBondt, 1993) or rather examine sentiment of investors for the US market exclusively (Kumar and Lee, 2006, Lee, Jiang and Indro, 2002, or Wang Keswani and Taylor, 2006).

Second, we contribute to the literature by directly extending a new empirical modelling approach from Brown and Cliff (2005) to the case of two investor groups. Earlier studies employing sentiment data have focussed on short run predictability in first or second moments (Lee, Jiang and Indro, 2002, Wang, Keswani and Taylor, 2006). Following Brown and Cliff (2005) we investigate longer term effects of sentiment on stock markets since the building up of excessive optimism or pessimism, i.e. sentiment, is likely to be a persistent process whose effects on stock prices would be hard to detect over short horizons of one or two months. Whereas Brown and Cliff limit their analysis to individuals, we jointly analyse the impact of both individuals and institutions on stock prices and complement their approach with further analyses that all point to the main result of this chapter: individual sentiment is a proxy for noise trader risk and institutions seem to be smart money.

The rest of the chapter unfolds as follows: the next section derives testable hypotheses from earlier studies and section 1.3 describes the data set. Section 1.4 shows results from long-horizon regressions, section 1.5 presents evidence from trading strategies based on sentiment, section 1.6 deals with the influence of individual sentiment on institutional investors and section 1.7 investigates structural stability. Section 1.8 concludes.

1.2 Hypotheses and earlier literature

One of the basic issues related to studies of investor sentiment deals with the question whether sentiment contains unique information for asset pricing. Indeed, there is lots of evidence that investor sentiment, moods or the awareness of investors for certain topics affect conditional moments of equity returns. This includes among others the high-volume premium documented by Gervais and Kaniel (2001), index additions and deletions (see e.g. Chen, Noronha and Singal, 2004) or rumors and talks in internet chatboards investigated by Antweiler and Frank (2003).

On a theoretical level, the model of Barberis, Shleifer and Vishny (1998) gives room for systematic under- and overreaction of stock returns due to shifts in investor sentiment. Using several proxies for investor sentiment Neal and Wheatley (1998) and Baker and Wurgler (2006) find that sentiment proxies heavily affect the cross-section of stock returns, e.g. that they affect the size effect or the relative prospects of different groups of stocks sorted by characteristics like volatility and dividend payments. These results seem to carry forward to the realm of real economic activity. Polk and Sapienza (2006) even find sentiment to have effects on the real economy by influencing managers' decisions to issue new shares when sentiment is high. Ang, Bekaert and Wei (2007) find survey measures of investor expectations to beat all traditional forecasting methods when predicting inflation in the U.S. which highlights the information contained in investor surveys. Therefore we expect that sentiment, as measured by genuine investor surveys, matters for stock returns for a period of intermediate to long horizons as in Brown and Cliff (2005) or Lemmon and Portniaguina (2006).

Since financial economists typically view individuals and institutions differently due to their relative size and sophistication and many researchers find that both groups often take opposite positions when trading (e.g. Kaniel, Saar and Titman, 2005) we expect sentiment of individuals to have a different effect than sentiment of institutions.

Regarding the nature of the difference between individuals and institutions, we observe that e.g. Barber, Odean and Zhu (2005), Brown and Cliff (2005), or Lemmon and Portniaguina (2006) find strong evidence for the hypothesis of excessive overoptimism which holds that noise traders who get overly optimistic (pessimistic) about a series of good (bad) news tend to push asset prices above (below) intrinsic values (see also Barberis, Shleifer and Vishny, 1998). Since many researchers view individuals as the proverbial noise traders (Kaniel, Saar and Titman, 2005) it implies that individual sentiment forecasts returns negatively, i.e. higher individual sentiment implies lower expected returns since asset prices eventually return to their fair values. Therefore our first hypothesis is, that individual investors' sentiment negatively predicts returns at longer horizons. Reliably identifying individual investors as noise traders has quite severe implications as outlined by Shleifer (2000). Individuals who have consistently wrong expectations should e.g. not be allowed to manage their own Social Security savings and their presence might hinder arbitrage that makes markets informationally efficient.

Evidence from trading data implies that institutions are informed investors (e.g. Chakravarty, 2001) although, as noted in the introduction, there is also evidence on non-sophisticated behavior of institutions like herding. However, for the functioning of financial markets there must be at least some market participants who collect and interpret fundamental information to calculate fair asset prices. Moreover, recent research indicates that the influence of fundamental risk factors on returns is state dependent and therefore needs to be interpreted by investors (see inter alia Bacchetta and van Wincoop, 2004, Boyd, Hu and Jagannathan, 2005 or Conrad, Cornell and Landsman, 2002). Since this is a demanding task, we would expect institutions due to their size and sophistication to fulfill this function. Therefore, we expect institutional sentiment to be positively correlated with expected stock returns, i.e. institutional sentiment correctly predicts market returns over longer horizons. This makes up our second hypothesis.

Finally, given that there is noise trader risk in financial markets, DeLong et al. (1990) show that equilibrium asset prices reflect a corresponding risk premium. Furthermore, smart investors should take into account the expected level and expected future changes in irrational sentiment (Shleifer, 2000). Therefore, we test whether institutions who expect a higher level of optimism (pessimism) by individuals get more pessimistic (optimistic) since they heed that noise traders have driven prices above (below) intrinsic values. This deviation from fundamentals has to be corrected eventually, so that a higher level of optimism (pessimism) by noise traders should decrease (increase) expected returns of smart investors. This sets up hypothesis 3a. Complementary to this test, we investigate whether institutional investors get more optimistic (pessimistic) when they expect individual sentiment to increase (decrease) over the near future. If increasing individual optimism drives stock prices up, rational institutions should take into account this relationship and expect higher (lower) returns when they expect individuals to become more bullish (bearish) over the near future. This is hypothesis 3b. The two hypotheses 3a and 3b are two sides of the same token. In the short run (hypothesis 3b), noise trader sentiment drives prices and smart money should rationally factor this relationship in when forming expectations which implies a positive relation between changes in institutional and changes in individual sentiment. Over longer horizons, deviations from fundamentals will eventually be corrected so that one should find a negative relation between changes of institutional sentiment and levels of individual sentiment (hypothesis 3a).

1.3 Data and descriptive statistics

We use data based on a weekly survey, called *sentix* (sentiment index). These are collected by "sentix - behavioral indices" and are available on the internet via www.sentix.de to frequent participants of the survey. They are also obtainable inter alia via Bloomberg, Thomson Financial, Ecowin or Reuters. The survey distinguishes between answers from institutional and individual investors. Although everybody who wishes to join-in the survey is allowed to, once registered online, there is an identity check in the case of institutional investors: Only investors who register with an e-mail address of an institutional investment firm (e.g. banks, brokers, asset managers) are allowed to vote for the category "institutional investor". Survey participation is not compulsory but frequent participation allows users to both access the time series of sentiment indices as well as special analyses by the operators of the survey - hence this provides an incentive to participate on a regular basis.

Participants are being asked anonymously what they think about the direction of the market upon short (one month) and medium (six months) horizons for several major stock markets in Europe, the USA and Japan. They can choose three answers, namely "up", "unchanged" and "down" for both time horizons separately. We centre our investigation upon the medium horizon answers[2] of both private and institutional investors for the DAX30 (DAX), EuroStoxx50 (ESX), NASDAQ100 (ND), S&P500 (SP) and Nikkei225 (NK).[3]

Our sample covers the period from February 23, 2001 to May 5, 2006 and consists of 263 observations, as some weeks were not evaluated due to official holidays

[2] As we find short run sentiment to be very noisy which confirms the results in Brown and Cliff (2004) or Wang, Keswani and Taylor (2006).

[3] There is data on one more market, the German TecDAX, which is similar to the NASDAQ indices. However, this index experienced a major reconstruction in the middle of the sample, consequently we do not use the data on this market.

taken place during this time. The number of responses in the survey totalled to 52 immediately after the start of the survey in February 2001 and steadily increased to 750 towards the end of the sample. The average response is 363 participants and the average share of institutional responses is about 25%. A disadvantage of the data is the relatively small number of respondents at the beginning of the survey in 2001. At this time, it would have been possible to manipulate the sentix index. However, this becomes more and more unrealistic towards the end of the sample with more than 700 survey respondents each week.

In order to make our data operational we first need a sensible measure to aggregate the survey answers. A common way to do this is to use the so-called *bull-bear-spread* (Brown and Cliff, 2004) which is computed by the number of positive minus negative answers divided by the total number of survey participants. We thus define our bull-bear-spread S_t^i for each of the five stock indices as

$$S_t^{i,m} = \frac{\#POS_t^{i,m} - \#NEG_t^{i,m}}{\#OBS_t^{i,m}} \tag{1.1}$$

where i denotes institutional $(i = I)$ or individual (or private, $(i = P)$) investors. The superscript m indicates the respective stock market, i.e. $m=$ DAX, ESX, ND, SP or NK. $\#POS_t$ ($\#NEG_t$) being simply the number of positive (negative) voters in week t. Finally, $\#OBS_t$ denotes the total number of survey participants in week t which is made up by positive, negative and neutral voters.

As a basic ingredient for the following analysis we also use log returns for each respective stock index. Descriptive statistics of the variables used can be found in **Table 1.1**. As one can see from Panel A of the table, stock returns display a typical behavior: they are not autocorrelated but show signs of heteroscedasticity. Panels B and C deal with institutional and individual investors' sentiment. In short, the mean and median of each series is positive and the maxima and minima are far from their natural bounds minus one and plus one. Thus, there are no really extreme aggregate expectations in the sample. Furthermore, all sentiment series are highly persistent as can be seen from the low test statistics of the Ljung-Box (1987) test who clearly reject the null of no autocorrelation. This persistent behavior of the series will be taken special care of in the following analysis. As one might expect, most sentiment series are highly non-normal as indicated by the Jarque-Bera test in the last two rows of each panel.

Figure 1.1 plots the evolution of the stock market index (right axis and bold dark line), individual (left axis and thin dark line) and institutional sentiment (left axis and thin grey line) for all five markets over the whole sample. As can be seen, the two sentiment indices covary negatively over the first half of the sample and mostly positively over the second half. Only for the NIKKEI 225 there seems to be a clear positive correlation between individual and institutional sentiment. Indeed, for the four European and US American markets, the correlation coefficients of individual and institutional sentiment are low between 0.10 and 0.25 whereas there is a correlation of roughly 0.80 for the Japanese market.

Finally, one might be concerned that the sentiment indices presented in Figure 1.1 are not only very persistent as indicated by the Ljung Box tests presented above but may even be unit-root nonstationary. Theoretically, there is a strong prior that the sentiment indices are stationary in the long run, because they are bounded between plus and minus one by construction. However, the series may well be nonstationary in a finite sample like ours. This poses a problem, because as it is well known, the question whether a time series has a unit root or is just very persistent is unanswerable in finite samples (see e.g. the discussion in Hamilton, 1994, p. 444-447). We present several unit-root tests for all ten sentiment indices in **Table 1.2**. On the 5% level, the null of a unit root is always rejected by the Phillips-Perron (1998) and Augmented Dickey-Fuller (1979) test. It is also rejected on the 10% level for all time series with the only exception being the institutional S&P500 sentiment when using the more recent DF-GLS test of Elliot, Rothenberg and Stock (1996). Therefore, the test results point towards stationarity although there is clear evidence of persistence in the time series. Since we are mainly interested in the information contained in the levels of sentiment[4], we will present analyses that explicitly take into account the high persistence in the sentiment indices. In section 1.5 we analyze trading strategies that are not subject to this problem and in section 1.6, we investigate an implication of the so obtained results on the first differences of sentiment indices. Encouragingly, all approaches yield results that are confirmative to each other.

[4]It is intuitive that e.g. a positive change in sentiment may have quite different effects on stock returns depending on whether the change occurs on a yet extremely bullish level or on a neutral level near zero.

1.4 Long-horizon return regressions

This section performs a simple and intuitive test for the existence of noise trader risk and smart money effects and establishes the main result of the chapter. Extending the empirical framework of Brown and Cliff (2005) to the case of two investor groups we run predictive regressions of stock returns on past sentiment of both individuals and institutions. The results show that individuals consistently forecast the wrong direction whereas institutional sentiment forecasts returns correctly.

1.4.1 Econometric methodology

We closely follow Brown and Cliff (2005) in the empirical setup to ensure comparability of our results. However, contrary to them we include both institutional and individual sentiment in our analysis to jointly test for the existence of noise trader risk and smart money. Towards this end we estimate long-horizon return regressions of the form

$$\frac{1}{k}\sum_{\kappa=1}^{k} r_{t+\kappa}^{m} = \beta_0^{(k),m} + \beta_1^{(k),m} S_t^{I,m} + \beta_2^{(k)} S_t^{P,m} + \Theta_t^m \gamma^{(k),m} + \varepsilon_t^{(k),m} \tag{1.2}$$

with the average $k-$period log return[5] for market m as endogenous variable and several predictors on the RHS. These predictors include sentiment of individual $S^{P,m}$ and institutional investors $S^{I,m}$ as well as typical macro and micro factors used in the asset pricing literature. These additional risk factors are collected in the matrix Θ and are detailed below. We employ known up-to-week t information to forecast cumulative excess returns beginning in week $t+1$ only.

Equation (**??**) can be used to test hypotheses 1 and 2 discussed in section 1.2. If sentiment matters for stock returns the coefficients β_1, β_2 should be nonzero. For the existence of noise trader risk and overoptimism among individuals (hypothesis 1) we expect $\beta_2^{(k)} < 0$ since overoptimism which pushes prices above intrinsic values eventually has to be reversed which implies that higher individual sentiment leads to low expected returns. For institutions to form correct expectations (hypothesis 2) $\beta_1^{(k)} > 0$ must hold, i.e. higher institutional sentiment is followed by higher returns. Since the regression approach measures net effects of each regressor (net of all other

[5]Using excess returns over the risk-free rate yields qualitatively identical results.

regressors) it is possible to determine if institutional sentiment correctly predicts market movements net of fundamental (Θ) risk factors and noise trader risk (S^P).

A common and nowadays well known problem with long-horizon regressions of the form above is, that they cannot simply be run by standard econometric tools even if robust covariance matrices are used. Several authors (see Stambaugh, 1999, Valkanov, 2003, or Ferson et al., 2003) have documented this problem, which is mainly caused by highly persistent regressors that evolve as stochastic processes themselves. In this case OLS estimation results are at best consistent but no longer unbiased although all regressors are predetermined. For simple regressions with only one predictor it can be shown analytically that the bias in coefficient point estimates increases, the stronger the persistence of the regressor gets (Stambaugh, 1999). As we show in Table 1.1 our sentiment indices are highly persistent.[6] A further complication arises from the overlapping of the sums of returns, which induces a moving average structure of order $k-1$ to the error terms $\varepsilon_t^{(k)}$.

Different ways have been proposed to circumvent these problems, mostly relying on some form of simulation procedure (see e.g. the application in Brown and Cliff, 2005) or auxiliary regressions (Amihud and Hurvich, 2004). In order to establish comparability with the results of Brown and Cliff (2005) we follow them by simulating small sample confidence intervals and test statistics for the coefficient estimates of each return regression separately to overcome this spurious regression problem (Ferson et al., 2003). The procedure used is described in the **Appendix**. There we also describe the ingredients to the matrix of control factors Θ which is slightly different across markets due to data availability for the respective countries.

1.4.2 Estimation results and interpretation

Results of this estimation-simulation procedure are depicted in **Figure 1.2**. The figure shows the estimated effect of a one standard deviation movement in institutional (left column of the figure) and individual (right column) sentiment for each horizon $k = 1, \ldots, 75$ weeks and simulated small sample 95% confidence intervals.

The results are clear-cut and confirm our hypotheses 1 and 2. Institutional investors' sentiment correctly predicts long-horizon index excess returns for most

[6] Brown and Cliff (2005) also find individual sentiment in the U.S. to have high serial correlation.

horizons in all five stock markets. Thus institutional investors are found to forecast future stock returns correctly if noise trader and fundamental risk is held fixed. This does not necessarily mean that their forecasts are always correct. It rather verifies that, on average and net of unpredictable factors, institutional sentiment gets the direction of future stock market movements right. This fits well for the assumption of institutions being rational arbitrageurs who collect and aggregate fundamental information since their sentiment contains information beyond that of several fundamental risk factors alone (which we include via Θ).

On the contrary, individual sentiment is negatively related with future stock returns although this relationship is significant mostly for longer horizons. This stands in line with the hypothesis that excessive optimism (pessimism) of noise traders drives prices above (below) fundamental values. These misvaluations eventually cause a subsequent reversal to intrinsic values so that individual sentiment and expected returns should indeed covary negatively. Thereby we confirm the findings of Barber, Odean and Zhu (2005), Brown and Cliff (2005) and Lemmon and Portniaguina (2006) for markets outside the U.S., namely that individual sentiment matters, that it covaries negatively with future returns and that the effects of individual sentiment take time to transmit to stock returns since excessive overoptimism (-pessimism) is a persistent process.

Interestingly, the results are very strong for institutional investors in all five markets, whereas the results for individual investors are best for the US, weaker for the two European markets and almost non-existent for Japan. According to the noise trader vs. smart money hypothesis this would imply that institutions are smart money in all countries (or regions) considered while the influence of noise traders is different for the different regions.

Since our investors are asked about their expectations regarding a six months horizon we also present estimation results of the two relevant parameters β_1 and β_2 for this horizon, i.e. $k = 24$ in **Table 1.3**. Reported are bias adjusted coefficients and p-values based upon simulated critical values for the t-test. We also report the percentage bias in coefficient estimates, denoted $\psi^{i,m}$[7], the simulated upper and lower critical values for the t-test on the 5% significance level, denoted t^u and t^l, and an analysis of the forecast root mean squared error (RSME) and Theil's U. It

[7]Remember that i indexes institutional (I) and individual (P) investors respectively.

can be inferred, that on this special forecasting horizon, that sentiment is significant for all four European and US markets whereas individual sentiment is significant only for the two US indices. Therefore, the most impressive results stand for the NASDAQ100 and S%P500 which have the highest R^2s, the highest covariance proportion of the root mean squared errors (RMSE) and the lowest p-values. However, it is unlikely that investors report exact "24 week" sentiment but rather their general medium term expectations. These might be based upon a somewhat longer or shorter period which would explain the strong results for other periods as presented in Figure 1.2. Finally, from a technical point of view, the simulated critical values for the t-statistics are much larger in absolute value than those employed in standard coefficient tests, which clarifies the need to adjust for the effects of persistent regressors.

The results shown in Figure 1.2 are also significant in economic terms and somewhat higher in absolute magnitude than those in Brown and Cliff (2005). There they find that a one standard deviation shock in sentiment leads to a cumulative decrease in excess returns of 7% over three years. We cannot examine this long horizons but our analysis shows that net effects of individuals over horizons of one year are approximately -10% whereas institutional sentiment has an effect of roughly +10% across markets. However, these results should not be interpreted easily as being evidence against the efficient markets hypothesis. First, there is large parameter uncertainty as can be seen from the rather wide standard errors in Figure 1.2 which might distract arbitrageurs from exploiting these relationships. Second, results for individual sentiment take a lot of time to be significant. These longer horizon could well be outside the usual investment horizon of many investors. Third, individual sentiment is likely to be a proxy for noise trader risk. Therefore, positive excess returns from a trading strategy based on sentiment should carry significant risk not captured by standard methods currently employed in practice (see Shleifer (2000) for a discussion of how risky it is to do arbitrage in the presence of noise traders). However, we implement a simple trading strategy based on the two sentiment series in the next section and indeed find signs of profitability when using standard techniques of controlling for risk.

1.5 Results based on sentiment trading strategies

This section investigates some easy to implement trading strategies for the sentiment and return series to examine whether the information contained in investor sentiment is exploitable. This serves to check the results from the long-horizon predictive regressions for robustness and to see whether the forecasting relationship between the two sentiment series and returns is likely to hold when leaving the specific in-sample regression context. As it turns out, even when the simplest possible strategies (which are not fitted or optimized in any way) are used, there is clear evidence of profitability.

When implementing trading strategies there is a danger of obtaining spurious results from overfitting and/or data-snooping, i.e. the researcher tries a wide range of possible strategies and reports only those strategies that yield results in favor of his null hypothesis. Although tests have been constructed to account for this bias (Sullivan, Timmermann and White, 1999) we employ a more robust way here by using the simplest possible trading strategies that are particularly easy to implement and that are based on the intuition of smart money and noise trader effects. Furthermore, we report results not for specific optimized parameters of the strategy but summary statistics for a wide range of plausible parameters.

Specifically, we report results for trading strategies based on the following simple algorithm for each market m:

1. Compute $\Omega_t^m = \frac{1}{1+k} \sum_{j=0}^{k} \left(S_{t-j}^{I,m} - S_{t-j}^{P,m} \right)$ where $k = 0, \ldots, 49$ weeks.
2. Hold the respective stock market index in week $t+1$ if $\Omega_t^m \geq 0$, i.e. earn the (log) market return r_{t+1}^m in week $t+1$.
3. If $\Omega_t^m < 0$ we consider two different possibilities:
    (a) Short the respective stock market index, i.e. earn $-r_{t+1}^m$ in week $t+1$. We refer to this as the "Long/Short strategy".
    (b) Hold a short term bond in week $t+1$, i.e. earn the risk-free rate $r_{t+1}^{f,m}$ in week $t+1$. We refer to this as the "Long strategy".

As mentioned above, we do not optimize the smoothing period k and we do not optimize by setting any thresholds which Ω_t^m has to surmount before generating trading signals.[8] The mechanics of the trading strategy have some additional nice properties namely that it (a) is easy to implement in practice and (b) is rooted in the economic intuition of the smart money and noise trader effects outlined above in this chapter. As we have argued, excessive optimism by noise traders implies lower expected returns (and vice versa) since stock returns will eventually return to fundamentals. Contrary to this, the expectations of smart money should correctly aggregate fundamental information, and thus get the direction of aggregate stock market movements right. Our strategy balances these two forces in the most simple way: Buy (sell) when institutional investors are more optimistic (pessimistic) than individuals.[9]

For each market m and each smoothing period $k = 0, \ldots, 49$ we compute weekly returns for (a) the Long/Short strategy, (b) the Long strategy, (c) a buy&hold portfolio that just holds the stock market index, and (d) a zero-cost strategy that is long in a trading strategy and short in the buy&hold portfolio. The zero-cost portfolio construction is common in finance (e.g. Jegadeesh and Titman, 2001) and serves to investigate whether completely self-financing trading strategies are profitable. For each of the so constructed weekly return series we calculate several statistics which are shown in **Table 1.4**.

Table 1.4, Panel A, shows results for the Long/Short strategies for all five markets. Since we have 50 results per market due to the different smoothing parameters k, $k = 0, \ldots, 49$, we report several summary measures. The mean $\bar{r} = (1/50) \sum_{k=0}^{49} \bar{r}_k$ gives the average mean return of all 50 strategies for each market which is about 8% p.a. Median $\bar{r}$ shows the median of the fifty mean returns. The measure $\% \bar{r} > 0$ shows the share of strategies that yield a positive mean return whereas $\sigma(\bar{r})$ reports the standard deviation of mean returns. Finally, mean σ and mean q_5 show the average of the fifty return standard deviations and five percent

[8] Doing so easily generates far more extreme figures of profitability than reported below. However, the results would be hard to interpret in terms of statistical and economic significance.

[9] According to this story, the most profitable situations should arise when institutional investors and individuals hold very different expectations. This can be easily incorporated into a trading strategy by constructing portfolios of stocks and bonds with time-varying investment shares depending on the disagreement between the two groups. Again, doing so may increase the profitability compared to the simple rule employed here but will be based on a more or less arbitrary rule for computing the portfolio shares.

points, respectively.

The first section shows results for the trading strategy whereas the second section shows results for the buy&hold strategy. As can be seen, the strategies based on the sentiment series consistently generate higher average and median mean returns than the buy&hold strategy. Compared to the latter, the trading strategies also tend to generate a higher percentage of mean returns that are larger than zero. Interestingly, the standard deviation of mean returns is higher for the trading strategy than for the buy&hold portfolio whereas the mean standard deviation and the mean five percent point are uniformly lower for the trading strategy than for holding the market portfolio. All in all, there is evidence in favor of the hypothesis that sentiment contains useful information for forecasting stock returns.

This is naturally confirmed by the third section which details results for the zero-cost portfolio. Average and median mean returns are positive for all markets and the shares of self-financing strategies that yield mean returns larger than zero range from 56% for the NIKKEI225 to 100% for the EuroStoxx50 and the NASDAQ100.

The fourth section shows some results regarding the statistical significance of risk-adjusted returns. The first row (median α) shows the median of Jensen's alpha estimated from the market model. The average and median alphas imply a weekly risk-adjusted excess return of about 0.2% per week which (roughly) translate into a risk adjusted return of ten percent p.a. However, the median t-statistic (median t_α) only ranges from about 1 to 1.8 which indicates that individual strategies (for fixed k) are not statistically significant. This is confirmed by the share of t-stats ($\%t_\alpha$ sign.) that is significant on the 5% level.[10] This share ranges from only 16% for the NIKKEI225 to 44% for the NASDAQ100. Also reported is the median of the estimated βs from the market model. The medians indicate that the betas are lower than unity. Therefore, the trading strategies do not seem to carry a lot of systematic risk.

Finally the last three rows show results for the median Sharpe ratios of the trading strategy (SR_{TS}) and the buy&hold portfolio (SR_{BH}). The median Sharpe Ratios of the trading strategies are uniformly higher than those for the buy&hold portfolio. The share of the 50 strategies that yield higher Sharpe ratios than the

[10] All test statistics are based on Newey-West HAC standard errors.

buy&hold portfolio ($\%(SR_{TS} > SR_{BH})$) is almost 100% for the four European and US American markets but significantly lower at 56% for the Japanese markets.

Panel B of Table 1.4 shows results for the Long strategy in the same manner as for the Long/Short strategy. The results are quite similar in the sense that the trading strategies considered tend to yield positive profits that are larger than for the buy&hold portfolio. Most notably, the percentage shares of significant alphas from the market model ($\%t_\alpha$ sign.) are higher than for the Long/Short strategy. Furthermore, the Sharpe ratios are somewhat smaller than those for the Long/Short strategy but the share of Sharpe ratios from the Long trading strategies that are higher than those of the buy&hold portfolio ($\%(SR_{TS} > SR_{BH})$) are slightly better than for the Long/Short strategy.

Transaction costs are unlikely to explain these findings. The trading strategies operate in highly liquid stock market indexes (the strategies would be implementable via futures) and not in illiquid stocks. As an example, adding rather high transaction costs of 0.5% per trade do not change our findings, since most strategies do not switch very often between long and short positions. However, a detailed analysis of more complex trading strategies and an exact evaluation of trading costs via microstructural data is beyond the scope of the chapter.

All in all, there is evidence that a strategy based on the two sentiment series might be profitable even after controlling for systematic risk in a standard way. Again, results for the US and Europe seem to dominate the results for Japan as documented above for the long-horizon regressions and in line with the findings of Chui, Titman and Wei (2005). The trading strategies might be best seen as a proxy for an out of sample test of the results obtained from long-horizon regressions. Here we do not optimize the strategy with sample information and show that a zero-cost trading strategy almost surely generates a higher expected profit than a buy and hold portfolio for the four European and US markets.

1.6 The effect of individual sentiment on institutional expectations

The results obtained by using bias-adjusted long-horizon regressions and the trading strategies indicate that individual sentiment is a proxy for noise trader risk and that institutional sentiment is conformable with expectations of smart traders who correctly aggregate fundamentals to form expectations. Given these results we would expect institutional investors to also take into account noise trader risk by individual investors (hypothesis 3a and 3b). This argument implies that the change in the sentiment of institutions should be affected by their expectations about the sentiment of individuals. We investigate this issue as a further plausibility check of our results obtained so far. Furthermore, since institutional sentiment seems to forecast aggregate market returns one might wonder if individual traders take advantage of this forecasting relationship and try to infer future institutional sentiment. If individual sentiment really represents noise, they should not exploit this presumably fundamentals based information contained in institutional investors' expectations.

In order to test these predictions, starting with hypothesis 3a, we estimate regressions of the following form:

$$\triangle S_t^{I,m} = \mu^{I,m} + \alpha^{I,m} S_t^{P,m} + \beta^{I,m}(L)\triangle S_t^{I,m} + \gamma^{I,m}(L) r_t^m + \varepsilon_t^{I,m} \tag{1.3}$$

$$\triangle S_t^{P,m} = \mu^{P,m} + \alpha^{P,m} S_t^{I,m} + \beta^{P,m}(L)\triangle S_t^{P,m} + \gamma^{P,m}(L) r_t^m + \varepsilon_t^{P,m} \tag{1.4}$$

where $\beta(L)$ and $\gamma(L)$ are polynomials in the lag operator and we are mainly interested in the parameter estimates of $\alpha^{I,m}$ and $\alpha^{P,m}$ whereas the remaining terms are included as control variables (see for example Wang, Keswany and Taylor (2006) for the importance of controlling for past returns).

Some comments regarding these equations are in order. First, putting the first difference of sentiment on the left hand side and the level of the other group's sentiment on the right hand side serves to estimate whether changes in institutional and individual sentiment can be explained by the level of the other group's sentiment as discussed above. Second, since the level of the other investor group's sentiment is unknown, and, more seriously, the regressions as stated above will suffer from simultaneity, we have to instrument for the level of sentiment in both equations. This IV approach also makes sense from an economic viewpoint, since we are essentially asking the following question for each of the two investor groups: how does my expectation of the other's group sentiment influence the change in my own sentiment? We do so by using as instruments all predetermined variables on the right hand side of the respective equations, i.e. lags of market returns and own changes in sentiment, and by further adding lagged levels of the sentiment we want to instrument for. As an example, consider the first of the above two equations concerning the change in institutional sentiment. Here we use lagged changes in institutional sentiment, lagged log returns and lagged values of individual sentiment $S_{t-1}^{P,m}, S_{t-2}^{P,m}, \ldots$. In order to free residuals from autocorrelation we use two lags of all variables. Estimation is carried out via GMM where t-values are based on Newey-West (1987) HAC standard errors.

The results are presented in **Table 1.5** and show that institutional investors (left part of the table) consistently adjust their sentiment downwards (upwards) when they expect individual sentiment to be high (low) which is consistent with the noise trader risk story of Brown and Cliff (2005) and Lemmon and Portniaguina (2006) as well as our hypothesis 3a. Furthermore, as can be seen from the right part of Table 1.5, individual investors do not take into account expected institutional sentiment, thereby neglecting relevant information.

A second implication of the noise trader story is, that optimism (pessimism) of these irrational investors drives stock values above or below intrinsic values. As in the model of DeLong et al. (1990) rational investors take into account these mechanism. Therefore, one should find that institutional sentiment rises (falls) if they expect individual investors' sentiment to become more optimistic (pessimistic) over the near future. We test this prediction via the following regression

$$\triangle S_t^{I,m} = \mu^{I,m} + \alpha^{I,m} \triangle S_{t,t+4}^{P,m} + \beta^{I,m}(L) \triangle S_t^{I,m} + \gamma^{I,m}(L) r_t^m + \varepsilon_t^{I,m} \tag{1.5}$$

which estimates the impact of expected changes in individual sentiment over the next four weeks $\triangle S_{t,t+4}^{P,m}$ on current institutional sentiment changes $\triangle S_t^{I,m}$. Again, we use GMM with Newey West HAC standard errors and the same set of instrumental variables as in equation (**??**).[11] Results are shown in **Table 1.6** and reveal that the estimated impact $\widehat{\alpha^{I,m}}$ is positive, statistically significant and of similar magnitude for all five markets, although the result for the NASDAQ100 is significant on the 10%-level only. This again is evidence in favor of the smart money vs. noise trader idea and confirms hypothesis 3b.

[11] Again, results for individual investors are not significant, so we omit them for the sake of brevity

1.7 Some stability considerations

A possible explanation for this puzzling finding might be, that individual investors need time to learn about the forecasting power of institutional sentiment for future stock returns as this relation was not obvious right from the beginning of this investor survey. Therefore, one might expect individual investors to rely more heavily on institutional sentiment towards the end of the sample when they had the chance to learn about the information contained in institutional sentiment. Indeed, taking a second look at Figure 1.1, it seems that both sentiment indices track each other more closely in the second half of our sample which might indicate a structural break.

Stability analyses for the long-horizon regressions are difficult since we need a long sample to reliably estimate these models and not just the last 100 observations or so. If we do estimate these models on the last 100 or 150 weeks anyway, we find somewhat weaker results than over the full sample. Although institutional sentiment still forecasts future excess returns, individual sentiment is no longer associated with statistically significant negative future returns. This clearly questions the validity of the noise trader risk story although the results for institutions being smart money is not affected.

A more direct investigation of structural stability can be carried out in the GMM regressions of the last section. We employ Wald tests put forward by Andrews (1993) and Andrews and Ploeberger (1994). The test for a structural break in their framework is briefly described below. The sample is divided into two subsamples according to a proportion π, $0 < \pi < 1$, so that the first subsample T_1 is made up by observations $1, \ldots, [\pi T]$ where T is the full sample and $[\pi T]$ denotes the integer part of πT. Thus, the second subsample consists of observations $[\pi T] + 1, \ldots, T$. The division in the two subsamples should obviously be guided by the structural break point to be tested. One then estimates the parameters of the model in the two subsamples and forms the Wald test statistic W_T according to

$$W_T(\pi) = \left[\hat{\beta}_1(\pi) - \hat{\beta}_2(\pi)\right]' \left\{\widehat{\mathbf{V}}_1(\pi) + \widehat{\mathbf{V}}_2(\pi)\right\}^{-1} \left[\hat{\beta}_1(\pi) - \hat{\beta}_2(\pi)\right]. \tag{1.6}$$

where β_1, β_2 denote the coefficient vectors for the two subsamples and $\mathbf{V}_1, \mathbf{V}_2$ denote the covariance matrices of the coefficients. However, since the timing of a possible structural break in our sample is a priori unclear, we rely on the method outlined in Anrdews (1993) and Andrews and Ploeberger (1994) and estimate the models detailed in (**??**) and (**??**) over different partitions of the sample. A common choice is to let π vary from 0.15 to 0.85 and to estimate the ingredients to (**??**) over these different subsamples to form a sequence of test statistics. The sequence can the be used to construct the Sup W_T (maximum of the test statistics), Avg W_T (average test statistic) and the Exp W_T statistic which is computed as

$$\text{Exp } W_T(\pi) = \ln\left[\frac{1}{\mathcal{R}}\sum_{r=1}^{\mathcal{R}} \exp\left[0.5W_T(\pi_r)\right]\right]. \tag{1.7}$$

where $\mathcal{R}$ is the number of sample partitions.

Results from these tests applied to the IV regressions of institutional sentiment changes on levels (**??**) and changes (**??**) in individual sentiment can be found in **Table 1.7**. As can be seen, there is ample evidence of structural change in the sample, especially for the two European markets DAX30 and EuroStoxx50. An inspection of the sequence of test statistics[12] reveals, that the structural break most likely takes place in the fourth quarter of 2003 for the European and Japanese markets and most likely in the middle of 2005 for the two US markets. For the European and Japanese markets this break might be due to the regime change from a bear to a bull stock market. However, this explanation does not fit the break for the US market which seemed to occur much later. Therefore, it is unclear what causes this structural instability and it will be interesting to see whether a longer time series of sentiment and stock returns or time series from other countries support or contradict the findings of this chapter. However, the instability uncovered here clearly weakens the earlier evidence (Brown and Cliff, 2005, Lemmon and Portniaguina, 2006) of smart money and noise trader risk for our sample.

1.8 Conclusion

Evidence on the role of individuals and institutions in financial markets is mixed. While several papers find evidence that individual sentiment proxies for noise trader risk (Barber, Odean, Zhu, 2005, Brown and Cliff, 2005, Kumar and Lee, 2006,

[12] Not shown here to conserve space

Lemmon and Portniaguina, 2006) there is rare evidence on genuine institutional sentiment. We jointly investigate sentiment from both institutions and individuals and find that (i) individuals seem to proxy for noise trader risk in a new data set and that (ii) institutional sentiment seems to proxy for smart money which confirms our first two hypotheses.

These results show up in both long-horizon regressions where we adjust for the disturbing effects of persistent regressors and also in the analysis of simple trading strategies . The former show that institutions (individuals) consistently have correct (incorrect) expectations for all five markets over medium horizons. The trading strategies show tendencies of being profitable on a risk-adjusted basis.

As a final check for plausibility of the noise trader interpretation of our results, we investigate cross effects of one group's sentiment on the change of the other group's sentiment. Consistent with the previous findings, a higher (lower) level of expected individual sentiment decreases (increases) institutional sentiment which fits the view that overly optimistic (pessimistic) noise traders have driven prices above (below) intrinsic values which will eventually cause a reversal in stock prices to correct this deviation from fundamentals. Furthermore, if institutions expect noise traders to become more optimistic (pessimistic) over short horizons they rationally incorporate this price pressure into their expectations and raise (lower) their sentiment which is in line with the behavioral finance literature and our hypothesis 3b.

Although there is lots of statistically and economically significant evidence of the noise trader vs. smart money view as in earlier papers, we find that structural stability is an issue. Especially the results for the influence of individual investors show clear signs of being subject to structural change. Their negative effect on future returns becomes statistically insignificant towards the end of the sample and institutional sentiment is no longer influenced by individual sentiment. This somewhat weakens the clear in-sample evidence. However, institutional sentiment still significantly forecasts stock returns later in the sample.

Appendix

The simulation procedure we employ is based on simulating new time series for each regressor to obtain bias adjusted confidence intervals for point estimates. Therefore we regress average excess returns on the two sentiment variables and control variables

$$\frac{1}{k}\sum_{\kappa=1}^{k} r^e_{t+\kappa} = \beta_0^{(k)} + \beta_1^{(k)} S_t^I + \beta_2^{(k)} S_t^P + \Theta_t \gamma^{(k)} + \varepsilon_t^{(k)} \tag{1.8}$$

where r^e_{t+1} is the market excess return over the risk-free rate from week t to $t+1$. For all five markets we investigate, the control variables in Θ include log changes in the respective countries' CPI and monetary aggregate M3 (the monetary base for Japan). We further include changes in dividend yields[13], short term (1 month) interest rates and the term spread (difference of yields for maturities of 10 years and 3 months) and the lagged market return. For the two US markets we further include the quality spread (difference of yields for bonds rated Baa and AAA) and the HML and SMB factors.

The simulation for each of the five stock market indices works as follows. We estimate a VAR(1)-Model that includes all variables in the above equation and imposes the null hypothesis that β_1 and β_2 are zero by setting the corresponding coefficients in the VAR to zero. The residuals are stored. Next, we bootstrap the residuals and recursively generate 10,000 new time series of the original length for all variables. With these simulated time series in hand we estimate equation (**??**) for horizons of $1, 2, \ldots, 60$ weeks and save the estimated coefficients $\widetilde{\beta}_1^{(k)}, \widetilde{\beta}_2^{(k)}$ for each horizon k over the 10,000 simulations. Note that the same 10,000 simulated time series can be used for every horizon. Standard errors of all regression coefficients in the simulation are corrected for autocorrelation up to lag $k-1$. This provides us with the empirical distribution of the point estimates which can in turn be used to perform bias-adjustments.

[13] Taken from Bloomberg, on a daily frequency.

Table 1.1 Descriptive Statistics

This table shows descriptive statistics for several variables employed in the empirical analysis separately for each stock market index. DAX denotes the DAX30, ESX the EuroStoxx50, ND stands for the NASDAQ100, SP for the S&P500 and NK for the NIKKEI225. Panel A shows statistics for log returns. $Q(10)$ denotes tenth order autocorrelation and the p-value for the Ljung-Box test statistic for autocorrelation up to the tenth order. $Q^2(10)$ shows the same statistics squared residuals. The residuals employed are filtered from an MA(1) model. JB gives the value of the Jarque-Bera test statistic computed with the filtered residuals described above to eliminate the effect of autocorrelation. Panel B and Panel C give the same statistics for institutional and private investors' sentiment. P-values are in parentheses.

Panel A: Return statistics

	DAX	ESX	ND	SP	NK
mean	0.000	0.000	-0.001	0.000	0.001
median	0.004	0.004	0.000	0.002	0.004
max.	0.129	0.136	0.206	0.075	0.095
min.	-0.139	-0.179	-0.192	-0.123	-0.077
std. dev.	0.034	0.031	0.041	0.023	0.028
skew	-0.243	-0.655	-0.049	-0.679	-0.090
kurt	4.853	7.879	6.669	7.359	2.826
$Q(10)$	0.068	0.037	0.053	0.088	0.075
	(0.09)	(0.39)	(0.41)	(0.35)	(0.93)
$Q^2(10)$	0.094	0.065	0.067	0.023	0.068
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
JB	40.055	278.570	147.065	227.564	0.686
	(0.00)	(0.00)	(0.00)	(0.00)	(0.71)

Panel B: Institutional sentiment statistics

	DAX	ESX	ND	SP	NK
mean	0.155	0.164	0.041	0.233	0.044
median	0.174	0.186	0.044	0.273	0.049
max.	0.476	0.452	0.389	0.633	0.400
min.	-0.156	-0.205	-0.286	-0.517	-0.350
std. dev.	0.131	0.133	0.119	0.205	0.114
skew	-0.351	-0.514	0.086	-0.701	-0.139
kurt	2.493	2.648	2.813	3.496	3.561
$Q(10)$	0.248	0.284	0.179	0.209	0.553
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q^2(10)$	0.035	0.073	0.043	0.078	0.162
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JB	8.230	12.956	0.711	24.242	4.293
	(0.02)	(0.00)	(0.70)	(0.00)	(0.12)

Table 1.1 (continued)

Panel C: Individual sentiment statistics

	DAX	ESX	ND	SP	NK
mean	0.111	0.121	0.042	0.036	0.162
median	0.098	0.108	0.041	0.034	0.211
max.	0.433	0.424	0.426	0.386	0.562
min.	-0.188	-0.184	-0.222	-0.229	-0.289
std. dev.	0.126	0.116	0.117	0.112	0.199
skew	0.336	0.250	0.364	0.174	-0.282
kurt	2.575	2.597	3.160	3.032	2.180
$Q(10)$	0.209	0.186	0.202	0.197	0.549
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q^2(10)$	0.158	0.107	-0.049	-0.023	0.017
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JB	6.942	4.522	6.080	1.340	10.853
	(0.03)	(0.10)	(0.05)	(0.51)	(0.00)

Table 1.2 Unit root tests for sentiment indices
This table shows unit root tests for the ten sentiment indices over the whole sample. PP denotes the Phillips-Perron test, ADF the Augmented Dickey Fuller test and DF-GLS is the Dickey Fuller test with GLS detrending. P-values are in parentheses.

	PP	ADF	DF-GLS
$S^{I,DAX}$	-8.267	-4.685	-3.074
	(0.00)	(0.00)	($<$ 0.01)
$S^{P,DAX}$	-5.821	-3.875	-1.677
	(0.00)	(0.00)	($<$ 0.10)
$S^{I,ESX}$	-8.364	-4.944	-2.278
	(0.00)	(0.00)	($<$ 0.05)
$S^{P,ESX}$	-5.631	-4.018	-2.704
	(0.00)	(0.00)	($<$ 0.05)
$S^{I,ND}$	-10.451	-6.126	-1.672
	(0.00)	(0.00)	($<$ 0.10)
$S^{P,ND}$	-6.087	-4.474	-2.914
	(0.00)	(0.00)	($<$ 0.01)
$S^{I,SP}$	-10.102	-6.331	-1.001
	(0.00)	(0.00)	($>$ 0.10)
$S^{P,SP}$	-6.278	-4.711	-2.542
	(0.00)	(0.00)	($<$ 0.01)
$S^{I,NK}$	-5.051	-3.67	-1.82
	(0.00)	(0.00)	($<$ 0.10)
$S^{P,NK}$	-3.411	-2.954	-2.914
	(0.01)	(0.04)	($<$ 0.01)

Figure 1.1 Sentiment and stock market indices
This figure shows the time series of stock market indices (thick dark line and right axis) and the time series of both individual (thin dark line and left axis) and institutional sentiment (thin grey line and left axis).

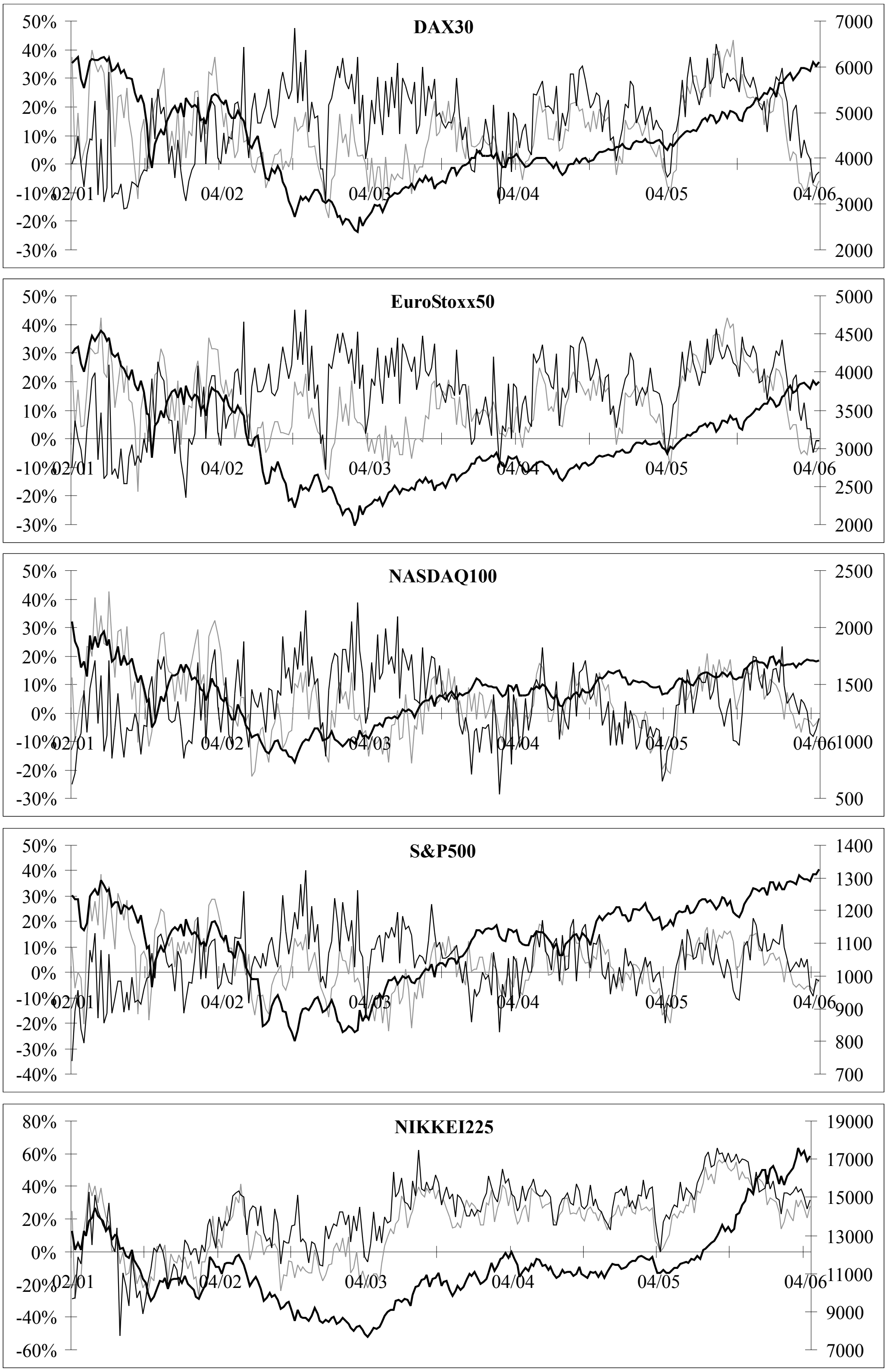

Figure 1.2 Long-horizon regressions at different horizons
This figure presents results from long-horizon regressions of excess returns on institutional and private sentiment as well as several other control factors. Displayed are the average weekly returns for one standard deviation movements in both sentiment variables for horizons up to 75 weeks. The left (right) side shows institutional (individual) sentiment. The vertical axis measures average log returns per week and the horizontal axis displays the horizon.

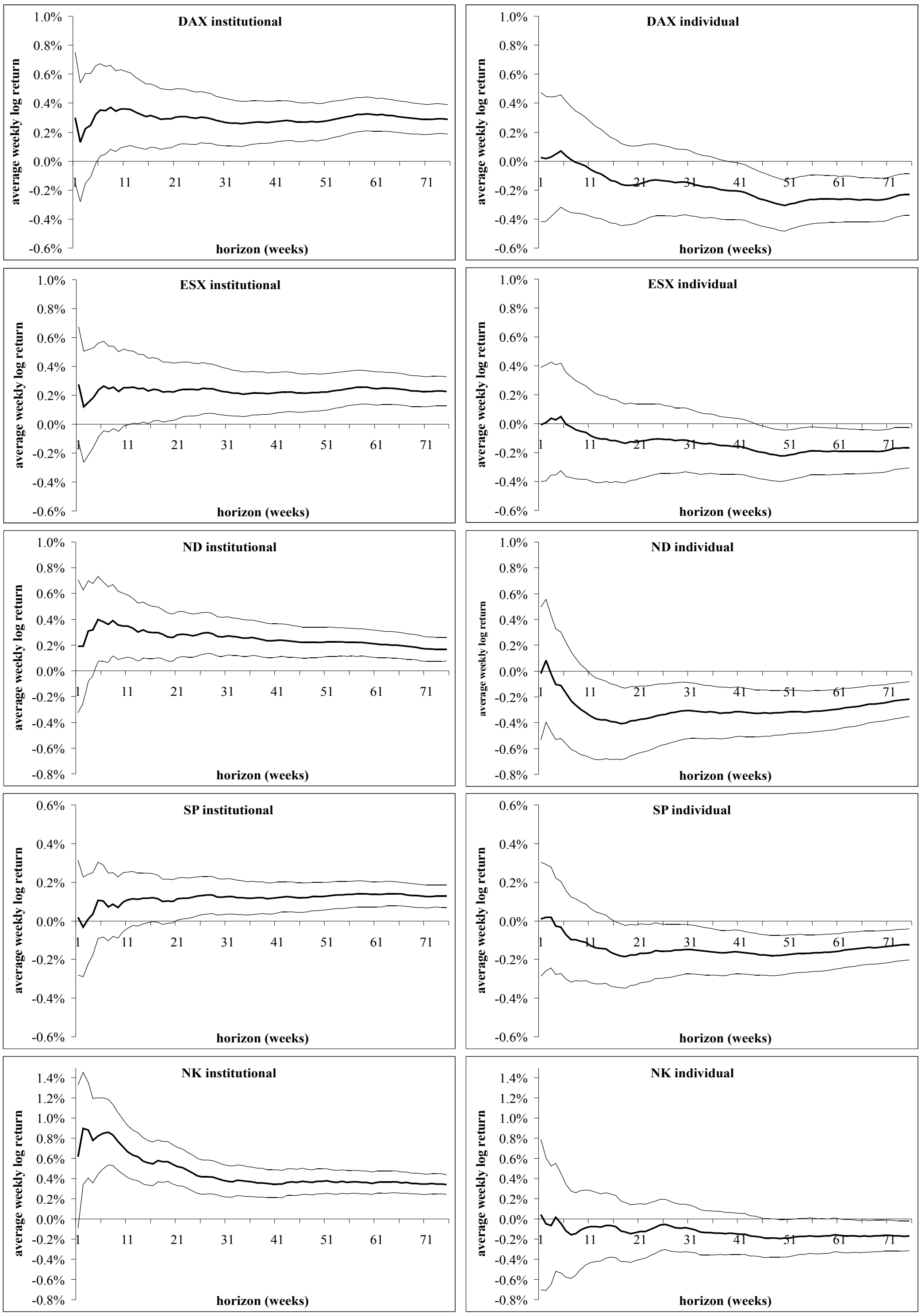

Table 1.3 Results from long-horizon regressions
This table shows results from long-horizon regressions of the form

$$\frac{1}{k}\sum_{\kappa=1}^{k} r_{t+\kappa}^{e,m} = \beta_0^{(k),m} + \beta_1^{(k),m} S_t^{I,m} + \beta_2^{(k),m} S_t^{P,m} + \Theta_t^m \gamma^{(k),m} + \varepsilon_t^{(k),m}$$

where $r^{e,m}$ is the (log) excess return for market m (m = DAX, ESX, ...), $S^{I,m}$ ($S_t^{P,m}$) is the sentiment index of institutional (individual) investors for market m, and Θ_t^m is time t vector of market specific control variables detailed in Appendix 1. k represents the horizon in weeks. The second column of the table shows bias-adjusted coefficient estimates of $\beta_1^{(k),m}$ and $\beta_2^{(k),m}$ for the horizon of $k = 24$ weeks along with p-values in parentheses which are based on the simulated small sample distribution of the test statistics. The fourth column shows the bias in the coefficient estimate ψ (in percent) whereas the fifth column shows simulated 5% critical values (t^l and t^u for the lower and upper critical value) for the null that the respective coefficient is zero. RMSE represents the root mean square error of the forecast, Bias %, Var. % and Covar. % show the decomposition of the RMSE and TU is Theil's U.

	coef.	adj. R^2	bias %	t^l / t^u			Theil's U
$S^{I,DAX}$	0.023		0.084	-2.362	RMSE	0.008	
	(0.026)	0.128		2.717	Bias %	0.000	0.672
$S^{P,DAX}$	-0.012		0.176	-2.633	Var. %	45.190	
	(0.536)			2.868	Covar. %	54.810	
$S^{I,ESX}$	0.018		0.060	-2.471	RMSE	0.006	
	(0.011)	0.140		2.583	Bias %	0.000	0.655
$S^{P,ESX}$	-0.009		0.163	-2.680	Var. %	43.583	
	(0.519)			2.928	Covar. %	56.416	
$S^{I,ND}$	0.023		-0.096	-2.742	RMSE	0.006	
	(0.001)	0.357		2.217	Bias %	0.000	0.495
$S^{P,ND}$	-0.030		-0.399	-3.408	Var. %	24.465	
	(0.013)			2.054	Covar. %	75.535	
$S^{I,SP}$	0.011		-0.021	-2.564	RMSE	0.004	
	(0.006)	0.263		2.418	Bias %	0.000	0.556
$S^{P,SP}$	-0.014		-0.259	-2.362	Var. %	31.123	
	(0.044)			2.717	Covar. %	68.877	
$S^{I,NK}$	0.022		-0.342	-3.597	RMSE	0.006	
	(0.155)	0.108		1.496	Bias %	0.000	0.686
$S^{P,NK}$	-0.004		-0.847	-4.763	Var. %	50.485	
	(0.649)			0.859	Covar. %	49.515	

Table 1.4 Trading Strategy results
This table shows results for trading strategies based on investor sentiment indices. Panel A shows results for the Long/Short strategy whereas Panel B shows results for the Long strategy.

PANEL A: LONG/SHORT STRATEGY

	DAX	ESX	ND	SP	NK
Trading strategy statistics					
mean $\bar{r}$	0.252	0.221	0.374	0.216	0.247
median $\bar{r}$	0.235	0.203	0.380	0.215	0.265
$\%\bar{r} > 0$	100%	100%	98%	98%	100%
$\sigma(\bar{r})$	0.113	0.096	0.124	0.077	0.100
mean σ	3.297	2.943	3.458	2.108	2.718
mean q_5	-5.821	-4.827	-5.336	-3.175	-4.484
Buy & hold strategy statistics					
mean $\bar{r}$	0.059	0.003	0.032	0.057	0.171
median $\bar{r}$	0.062	0.010	0.030	0.059	0.181
$\%\bar{r} > 0$	80%	56%	72%	100%	100%
$\sigma(\bar{r})$	0.052	0.041	0.054	0.027	0.058
mean σ	3.308	2.953	3.480	2.120	2.725
mean q_5	-6.103	-5.180	-6.051	-3.326	-4.606
Zero-cost strategy statistics					
mean $\bar{r}$	0.193	0.217	0.341	0.159	0.076
median $\bar{r}$	0.179	0.200	0.341	0.154	0.062
$\%\bar{r} > 0$	96%	100%	100%	98%	56%
$\sigma(\bar{r})$	0.103	0.085	0.139	0.078	0.154
mean σ	3.818	3.734	5.498	2.959	1.997
mean q_5	-4.154	-3.719	-8.296	-3.735	-0.153
Summary test statistics					
median α	0.224	0.204	0.369	0.218	0.110
median t_α	1.047	1.238	1.835	1.628	1.025
$\%t_\alpha$ sign.	18%	30%	44%	28%	16%
median β	0.298	0.186	-0.270	0.036	0.722
SR_{TS}	0.054	0.052	0.095	0.083	0.097
SR_{BH}	0.005	-0.014	-0.003	0.009	0.068
$\%(SR_{TS} > SR_{BH})$	96%	100%	100%	98%	56%

Table 1.4 (continued)

Panel B: Long Strategy	DAX	ESX	ND	SP	NK
Trading strategy statistics					
mean $\bar{r}$	0.170	0.127	0.230	0.155	0.209
median $\bar{r}$	0.165	0.130	0.229	0.168	0.213
$\%\bar{r} > 0$	100%	100%	100%	100%	100%
$\sigma(\bar{r})$	0.067	0.056	0.066	0.042	0.028
mean σ	2.683	2.269	2.110	1.504	2.528
mean q_5	-4.683	-4.169	-3.158	-2.468	-4.406
Buy & hold strategy statistics					
mean $\bar{r}$	0.059	0.003	0.032	0.057	0.171
median $\bar{r}$	0.062	0.010	0.030	0.059	0.181
$\%\bar{r} > 0$	80%	56%	72%	100%	100%
$\sigma(\bar{r})$	0.052	0.041	0.054	0.027	0.058
mean σ	3.308	2.953	3.480	2.120	2.725
mean q_5	-6.103	-5.180	-6.051	-3.326	-4.606
Zero-cost strategy statistics					
mean $\bar{r}$	0.110	0.123	0.198	0.098	0.038
median $\bar{r}$	0.105	0.117	0.202	0.096	0.031
$\%\bar{r} > 0$	98%	100%	100%	98%	56%
$\sigma(\bar{r})$	0.049	0.040	0.069	0.039	0.077
mean σ	1.913	1.871	2.749	1.480	0.998
mean q_5	-2.024	-1.808	-4.108	-1.804	-0.076
Summary test statistics					
median α	0.152	0.141	0.227	0.147	0.055
median t_α	1.403	1.675	2.389	2.217	1.034
$\%t_\alpha$ sign.	30%	34%	80%	62%	16%
median β	0.648	0.592	0.364	0.517	0.861
SR_{TS}	0.044	0.037	0.097	0.089	0.084
SR_{BH}	0.005	-0.014	-0.003	0.009	0.068
$\%(SR_{TS} > SR_{BH})$	100%	100%	100%	98%	58%

Table 1.5 The effect of expected sentiment levels on sentiment changes

This table shows results from GMM regressions of the form

$$\triangle S_t^{I,m} = \mu^{I,m} + \alpha^{I,m} S_t^{P,m} + \beta_1^{I,m} \triangle S_{t-1}^{I,m} + \beta_2^{I,m} \triangle S_{t-2}^{I,m} + \gamma_1^{I,m} r_{t-1}^m + \gamma_2^{I,m} r_{t-2}^m + \varepsilon_t^{I,m}$$

and

$$\triangle S_t^{P,m} = \mu^{P,m} + \alpha^{P,m} S_t^{I,m} + \beta_1^{P,m} \triangle S_{t-1}^{P,m} + \beta_2^{P,m} \triangle S_{t-2}^{P,m} + \gamma_1^{P,m} r_{t-1}^m + \gamma^{P,m} r_{t-2}^m + \varepsilon_t^{P}$$

where $S_t^{I,m}$ ($S_t^{P,m}$) is institutional (individual) sentiment of week t for market m and r^m is the return of the respective stock market index ($m =$ DAX, ESX, ...). For each equation, instruments consist of the exogenous variables and two lags of the endogenous variable ($S_t^{I,m}$ or $S_t^{P,m}$). P-values in parentheses are based on Newey-West HAC standard errors and $Q(10)$ reports the tenth order autocorrelation and the p-value for the Ljung-Box test statistic at the tenth lag and $Q^2(10)$ reports the same statistics for squared residuals at lag ten (p-values in parenthesis).

	DAX	ESX	ND	SP	NK		DAX	ESX	ND	SP	NK
const.	0.013	0.016	0.007	0.004	0.011	const.	0.005	0.004	0.002	0.004	0.014
	(0.197)	(0.128)	(0.281)	(0.479)	(0.228)		(0.626)	(0.719)	(0.667)	(0.559)	(0.131)
$S^{P,m}$	-0.129	-0.143	-0.135	-0.135	-0.061	$S^{I,m}$	-0.040	-0.031	-0.069	-0.097	-0.057
	(0.029)	(0.025)	(0.035)	(0.030)	(0.078)		(0.471)	(0.569)	(0.369)	(0.330)	(0.062)
$\triangle S_{-1}^{I,m}$	-0.544	-0.508	-0.570	-0.545	-0.486	$\triangle S_{-1}^{P,m}$	-0.292	-0.356	-0.359	-0.385	-0.347
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\triangle S_{-2}^{I,m}$	-0.165	-0.167	-0.208	-0.197	-0.121	$\triangle S_{-2}^{P,m}$	0.030	-0.080	-0.023	-0.151	0.067
	(0.032)	(0.027)	(0.004)	(0.006)	(0.077)		(0.708)	(0.339)	(0.770)	(0.034)	(0.463)
r_{-1}^m	0.036	0.236	0.136	0.503	0.236	r_{-1}^m	0.165	0.216	0.225	0.436	0.593
	(0.837)	(0.184)	(0.407)	(0.019)	(0.390)		(0.312)	(0.208)	(0.191)	(0.141)	(0.028)
r_{-2}^m	-0.054	-0.275	-0.077	-0.181	-0.161	r_{-2}^m	-0.075	0.018	-0.067	0.051	0.049
	(0.732)	(0.120)	(0.718)	(0.538)	(0.567)		(0.650)	(0.903)	(0.728)	(0.822)	(0.824)
adj. R^2	0.181	0.170	0.210	0.173	0.162	adj. R^2	0.050	0.070	0.043	0.051	0.044
$Q(10)$	0.019	0.077	0.093	0.107	0.03	$Q(10)$	-0.142	-0.152	-0.082	-0.052	0.073
	(0.882)	(0.531)	(0.105)	(0.183)	(0.521)		(0.105)	-0.033	(0.398)	(0.672)	(0.384)

Table 1.6 The effect of expected individual sentiment changes on institutional sentiment

This table shows results for GMM regressions of institutional sentiment changes on expected changes in individual sentiment over the next four weeks (see equation (5)). P-values in parentheses are based on Newey-West HAC standard errors and $Q(10)$ reports the tenth order autocorrelation and the p-value for the Ljung-Box test statistic at the tenth lag and $Q^2(10)$ reports the same statistics for squared residuals at lag ten (p-values in parenthesis).

	DAX	ESX	ND	SP	NK
const.	0.001	0.001	0.003	0.001	0.002
	(0.903)	(0.795)	(0.607)	(0.804)	(0670)
$\triangle S_{+4}^{P,m}$	0.394	0.408	0.347	0.348	0.346
	(0.008)	(0.007)	(0.059)	(0.045)	(0.036)
$\triangle S_{-1}^{I,m}$	-0.536	-0.519	-0.590	-0.570	-0.488
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\triangle S_{-2}^{I,m}$	-0.180	-0.192	-0.241	-0.240	-0.135
	(0.033)	(0.014)	(0.001)	(0.002)	(0.083)
r_{-1}^{m}	0.352	0.519	0.381	0.896	0.200
	(0.096)	(0.022)	(0.046)	(0.003)	(0.462)
r_{-2}^{m}	0.102	-0.107	0.075	0.070	-0.068
	(0.605)	(0.609)	(0.790)	(0.847)	(0.829)
adj. R^2	0.079	0.108	0.131	0.084	0.013
$Q(10)$	0.013	0.054	0.079	0.083	0.066
	(0.345)	(0.174)	(0.054)	(0.114)	(0.005)

Table 1.7 Tests for Model Stability

Tests of structural stability for the IV regressions. Stars refer to the level of significance: ***, **, *: $\alpha = 0.01, 0.05, 0.10$. Significance results are based on Table 1 in Andrews (1993) and Table 1 and 2 in Andrews and Ploeberger (1994).

	DAX	ESX	ND	SP	NK
Expected sentiment levels					
Avg $W_T(\pi)$	***22.70	***20.64	8.05	8.82	7.16
Sup $W_T(\pi)$	***44.08	***42.42	***34.70	***27.16	13.29
Exp $W_T(\pi)$	***39.50	***36.96	***28.91	***21.83	***9.63
Expected sentiment changes					
Avg $W_T(\pi)$	***13.25	***17.71	5.96	5.64	*6.206
Sup $W_T(\pi)$	***29.93	***47.53	***31.73	14.70	11.85
Exp $W_T(\pi)$	***25.53	***41.87	***26.07	***10.42	**8.44

Chapter 2:
Investor sentiment, herd-like behavior and stock returns: Empirical evidence from 18 industrialized countries

2.1 Introduction

The recent literature has seen a rise of studies investigating the effect of individual investor sentiment on stock returns. Several papers document a strong link between the two variables both in the time series and cross-sectionally. These papers estimate predictive regressions of the form

$$r_{t+1} = \alpha + \beta \cdot \text{sentiment}_t + \eta_t \tag{2.1}$$

where r_{t+1} is the return of the aggregate stock market or a (zero-cost) portfolio at time $t+1$ and $sentiment_t$ is a proxy for (lagged) investor sentiment. A common finding for the US stock market is a statistically and economically significant negative coefficient estimate for β. Therefore, periods of higher investor optimism tend to be followed by significantly lower returns for the aggregate market (e.g. Brown and Cliff, 2005) and even more pronouncedly for firms that are hard to price and thus difficult to arbitrage (e.g. Baker and Wurgler, 2006, Lemmon and Portniaguina, 2006).

In order to assess the relation of sentiment and returns out-of-sample, we investigate whether consumer confidence – as a proxy for individual investor sentiment – affects stock returns along the lines of (2.1) in 18 countries internationally. We find, first, that for about half of the markets considered, there is a significant impact of investor sentiment on aggregate stock returns even after controlling for commonly employed macro risk factors as in Brown and Cliff (2005). Second, in cross-sectional regressions we provide some first evidence that the impact of sentiment on stock returns is stronger in countries in that are culturally more prone to herd-like behavior as predicted by Chui, Titman and Wei (2005). The effect also seems to be stronger in countries with less efficient markets.

The general finding of a sentiment-return relation is at odds with standard finance theory which predicts that stock prices reflect the discounted value of expected cash-flows and that irrationalities among market participants will be erased by arbitrageurs. Sentiment does not play any role in this classic framework. The behavioral approach instead suggests that waves of irrational sentiment, i.e. times of overly optimistic or pessimistic expectations, can persist and affect asset prices for significant time spans. DeLong et al. (1990) show in their seminal paper, that correlated sentiment of irrational investors is a priced risk factor. Assets with higher levels of noise trader risk have higher expected returns. Thus, there is both empirical evidence for a link between sentiment and stock returns and a sound theoretical underpinning of this relationship.

On the available empirical evidence for the US, overlooked rational factors that drive the relation between sentiment and stock returns are a possible but less and less likely explanation. Several authors (Baker and Wurgler, 2006, Brown and Cliff, 2005, Kumar and Lee, 2006, Lemmon and Portniaguina, 2006, Hvidkjaer, 2006 to name just a few) document empirically that the link between sentiment and future returns is most likely due to overly optimistic (pessimistic) investors who drive prices above (below) intrinsic values, a misevaluation that is corrected eventually and leads to the observed negative influence of sentiment on stock returns. Data mining is a somewhat more likely possibility. There is little evidence for this relationship outside the US so that the effects of sentiment on returns might well be a statistical artifact. Out-of-sample tests of an anomaly are one means to investigate this possibility.[14]

Therefore, we investigate the link between asset prices and investor sentiment for 18 industrialized countries around the world. "Geographical" out-of-sample tests are a common way to amass or to weaken earlier evidence (e.g. Ang, Hodrick, Xing, and Zhang, 2006, Griffin, Ji, and Martin, 2003). This is the first major contribution of this chapter. Furthermore, to assess the behavioral explanation from a different viewpoint, we also examine whether cross-sectional variation in demographic, cultural and market efficiency related factors systematically affects the magnitude of the link between sentiment and stock returns. To the best of our knowledge, we are the first to investigate this issue and this makes up the second major contribution of the chapter.

The investigation whether cultural factors play a role is motivated by the paper of Chui, Titman and Wei (2005) who investigate whether individualism as measured by Hofstede (2001) is a cross-country determinant of momentum profits. The authors argue that countries with a more individualistic culture are more prone to certain behavioral biases that benefit the existence of momentum profits. Their findings support

[14] Jackson (2003) finds no evidence for short-run reversals after waves of optimism and pessimism for Australia for the period 1991 - 2002. Schmeling (2006) finds evidence of such reversals for Germany for a period spanning 2001 to 2006.

this hypothesis. As for the case considered here, if the impact of investor sentiment on stock returns is truly due to correlated behavior of irrational traders, one should expect this effect to be higher in countries that are collectivistic since collectivism boosts “herd like overreaction” (see Chui, Titman and Wei, 2005, p.28). Therefore, an alternative test of the implicit assumption that the effect of sentiment on stock returns is due to overreaction on the part of noise traders and not due to time-varying fundamental risk factors can be conducted by investigating whether the sentiment-return relationship varies according to this cultural dimension cross-sectionally between different countries.

As noted above, we also check whether institutional quality or informational efficiency of a country explains the cross-section of the sentiment-return relation. We find some evidence for this hypothesis although less pronounced than for the cultural factors. Therefore, this chapter also contributes to a growing literature that cross-sectionally relates market outcomes to market institutions (cf. La Porta et al. 1998).

The plan of action is as follows. The next section selectively reviews the existing literature. Section 2.3 describes the data and provides some descriptive statistics. Section 2.4 provides estimates of predictive regressions of returns on sentiment similar to equation (2.1). Section 2.5 investigates cross-country results and section 2.6 concludes.

2.2 Literature review

As Baker and Wurgler (2006, p. 1648) point out, “a mispricing is the result of both an *uninformed demand* shock and a *limit to arbitrage*” (emphasis added). Regarding the first ingredient, uninformed demand shocks, Brown and Cliff (2005) argue that sentiment is most likely a very persistent effect so that demand shocks of uninformed noise traders may be correlated over time to give rise to strong and persistent mispricings. However, the second ingredient, limits of arbitrage, deter informed traders from eliminating this situation (cf. Black, 1986, or more formally, Shleifer and Vishny, 1997) since it is a priori unclear how long buying or selling pressure from overly optimistic or pessimistic noise traders will persist. However, every mispricing must eventually be corrected so that one should observe that high levels of investor optimism are on average followed by low returns and vice versa.

As discussed in the introduction, there is now substantial empirical evidence for the U.S that (proxies for) investor sentiment indeed forecast stock returns negatively in the time series (cf. Brown and Cliff, 2005, Lemmon and Portniaguina, 2006).

An influence of sentiment is also found in the cross-section of U.S. stock returns. Baker and Wurgler (2006) document that those stocks are more affected by shifts in sentiment that are (a) hard to value because valuations are highly subjective and (b) for those stocks that are hard to arbitrage. Indeed they find that sentiment effects are stronger among stocks that can reasonably be assumed to fulfill at least one of these criteria, e.g. young, small, unprofitable, distressed, extreme growth or dividend-nonpaying firms. For the U.S. this finding for distressed stocks is underscored by the finding of Kumar and Lee (2006) who show that retail investors, which are commonly thought of being noise traders (Kaniel, Saar and Titman, 2005), tend to overweight value stocks relative to growth stocks and that shifts in the buy-sell imbalance of these retail investors are positively correlated with returns of value stocks. This clearly is a prime example of noise trader risk.

Also in this spirit, Barber, Odean and Zhu (2005) investigate returns of stocks that are heavily bought and sold by U.S. individual retail traders and provide somewhat even more direct evidence on the story that individuals are noise traders. They show that stocks heavily sold by individuals outperform stocks heavily bought by a hefty 13.5% the following year. They also document strong herding among individual investors so that the notion of correlated trading by irrational investors seems to be a likely cause for these return differentials. Hvidkjaer (2006) sorts stocks from NYSE, AMEX and NASDAQ based on past difference between sell and buy volume from small trades, i.e. trades that most likely come from individual traders. He finds that stocks with large individual selling pressure outperform stocks with large individual buying pressure over horizons of up to three years. Depending on the sorting procedure, Hvidkjaer (2006) tends to find large return differences of up to 0.94% per month for a portfolio long in stocks that have been sold most heavily by individuals over the last 6 months and short in stocks that have most heavily been bought by individuals over the last 6 months. As with the results from Barber, Odean and Zhu (2005), these numbers suggest that irrational trading of noise traders is an important determinant of expected stock returns.

A natural question that arises when attempting to quantify the influence of sentiment on stock returns is how to measure (unobserved) sentiment? Existing studies have used different proxies, of which closed-end fund discounts are one major vehicle (c.f. Lee, Shleifer, and Thaler, 1991, or Neal and Wheatley, 1998). Baker and Wurgler (2006) construct a sentiment proxy from several market price based variables such as closed-end fund discounts, number of IPO's, turnover etc. Recent studies have started to use micro trading data, such as Kumar and Lee (2006) who use broker data or Barber, Odean and Zhu (2005) who use the TAQ/ISSM data. Finally, some studies use data from investor surveys (cf. Brown and Cliff, 2005). Charoenrook (2005) and Lemmon and Portniaguina (2006) use consumer confidence indexes to proxy for sentiment, based on the observation that Brown and Cliff (2004) find no evidence that closed-end fund discounts reflect sentiment and that Qiu and Welch (2005) report only weak correlation of these fund discounts with UBS/Gallup surveys of investor sentiment. The consumer confidence indexes do better in this respect. Furthermore, Fisher and Statman (2003) provide evidence that consumer confidence correlates well with other sentiment proxies such as the sentiment measure from the American Association of Individual Investors (AAII) whereas Doms and Morin (2004) find that consumer confidence contains an irrational element since it responds to the tone and volume of economics news reports while being hardly affected by the content of news. All these findings make consumer confidence seem to be a reasonable proxy for individual sentiment and we follow these findings by using measures of consumer confidence as a sentiment proxy throughout the chapter.

Finally, given the accumulated evidence of the influence of sentiment on returns the question remains whether one should expect this relation to hold outside the U.S. as well. Evidence from a different market anomaly based most probably on behavioral biases by market participants, namely the abnormal size of momentum profits documented by Jegadeesh and Titman (1993), suggests that this does not necessarily need to be the case. Momentum profits, though large and significant in the U.S. and most of Europe (Rouwenhorst, 1998), are completely absent in Japan and almost non-existent in the rest of Asia.

Recently, Chui, Titman and Wei (2005) propose that cultural differences might play a role for the relative strength of behavioral biases between countries.[15] Specifically, they argue that individualism as measured by Hofstede (2001) drives certain behavioral biases that are assumed to generate the apparent momentum profits.

[15] Guiso, Sapienza and Zingales (2006) and Chuah et al. (2006) document that culture may significantly affect economic outcome although yet little attention has been paid to these factors in economics. However, there seems to be even less empirical evidence for the role of culture in finance than in economics.

The authors also argue that a lack of individualism, i.e. collectivism, might drive certain biases "that generate even more important market inefficiencies" (p. 28) than the momentum premium. Collectivistic countries have societies in which people are integrated into strong groups and, as such, "may place too much weight on consensus opinions, and may thus exhibit *herd-like overreaction* …" (emphasis added). Herd-like overreaction, i.e. correlated actions of noise traders based on overly optimistic or pessimistic expectations, is precisely what is assumed to drive the sentiment-return relation in financial markets. Therefore, one may expect that collectivistic countries show a stronger impact of sentiment waves on returns whereas individualistic countries, in which people tend to put more weight on their own information and opinion, should be less affected by these behavioral biases.

2.3 Data and descriptive statistics

As noted above, we are interested in measuring the effect of noise trader demand shocks on stock markets. Doing this in a consistent way is exacerbated by the fact that there is no consensus on what kind of proxies to employ when measuring individual sentiment for a single country. This problem naturally aggravates when attempting to find a proxy that is available for different countries.

However, given the recent detailed analysis of consumer confidence as measure for investor sentiment by Lemmon and Portniaguina (2006) it seems natural to use this metric for an international analysis. First of all, consumer confidence is available for several industrialized countries and, second, it is available for reasonable time spans. Third, consumer confidence, albeit measured slightly different in various countries, seems to be the only consistent way to obtain a sentiment proxy that is largely comparable across countries.

Therefore, we use data on stock returns and consumer confidence for 18 industrialized countries around the globe to investigate the sentiment-return relation internationally. Our sample of countries is largely dictated by data availability but consumer confidence is available for several countries on horizons of up to 20 years. We include the U.S., Japan, Australia, New Zealand and 14 European countries (see **Table 2.1** for a complete list of countries). These markets cover the lion's share of international stock market capitalization, cover the most liquid markets in the world - namely the U.S., Europe and Japan - and thus provide a representative sample.

Consumer sentiment for the European countries is available from a single source so the comparability of sentiment data is especially attractive for this large sub-sample of countries.

For each of the 18 countries we collect a monthly measure of consumer confidence, monthly returns for (a) the aggregate stock market, (b) a portfolio of value stocks and (c) a portfolio of growth stocks.[16] We investigate aggregate market returns as well as value and growth stocks for the following reasons. First, there is evidence (Baker and Wurgler, 2006) that sentiment affects the cross-section of returns differently for different investment styles, e.g. value and growth. Second, Shiller (2001, p.243) quotes Paul Samuelson with the following claim: "I [hypothesize] considerable *macro* inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values." Therefore, it seems to make sense to look for these macro inefficiencies in aggregate market returns, too.

Stock market data come from Prof. Kenneth French's web site and are employed because they are collected in a consistent manner across countries, are relatively free of survivorship bias (Fama and French, 1998) and were used in other studies before (e.g. Chui, Titman and Wei, 2005, motivate their herding and collectivism result with this data).

Furthermore, for each country we collect data on consumer confidence. For all 14 European countries the data comes from the "Directorate Generale for Economic and Financial Affairs" (DG ECFIN)[17] which, among other things, conducts research for the European Union. Confidence indices for the remaining countries are obtained from Datastream. There are several possible high-quality consumer confidence indices for the U.S. We employ the Michigan Survey (see Lemmon and Portniaguina, 2006). Finally, the consumer confidence index for Japan is available on a quarterly frequency only. We convert it to a monthly frequency by using the last available values for months without data as in Baker and Wurgler (2006).

Table 2.1 provides descriptive statistics for returns and consumer confidence indices. Column three shows the time spans available for each country. We include the time from January 1985 to December 2005 wherever possible. Data limitations enforce

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[16] Stock market returns are from value-weighted portfolios in local currency. The value portfolio consists of the top three deciles of stocks sorted by B/M whereas the growth portfolio comprises the bottom 30% of stocks sorted by B/M.

[17] These consumer confidence indices have also been used by Jansen and Nahuis (2003). Data can be downloaded from: *http://ec.europa.eu/economy_finance/indicators_en.htm*.

somewhat shorter periods for several countries. However, we have a minimum of 120 monthly observations even for the most data-constrained country Austria.

As can be seen, value stocks have higher mean returns than growth stocks for most countries, a fact documented before in a voluminous literature on the so-called value premium (Fama and French, 1998). The descriptive statistics for the consumer confidence indices show a high degree of serial correlation in the time-series. First order autocorrelations (ρ_{-1}) are extremely high and uniformly above 90%. We will take special care of this high serial correlation in our empirical analyses.

Table 2.2 shows correlation coefficients of the consumer confidence above the main diagonal and correlations for monthly changes in consumer confidence below the main diagonal. As can be seen from both the correlation coefficients computed in levels and in changes, the comovement across countries is not prohibitively strong, i.e. we are not using essentially one sentiment series. There are several countries that show a large correlation (e.g. Austria and Germany), essentially no correlation (e.g. Australia and Switzerland) or a negative correlation (e.g. Sweden and Japan).

2.4 Predictive regressions of stock returns on consumer confidence

2.4.1 Methodology

Brown and Cliff (2005) argue that the building up of overly optimistic or pessimistic views is a persistent process which might not be detectable over short horizons. Information about the degree of optimism or pessimism is contained in sentiment levels rather than changes. Therefore, it is necessary to measure the impact of past sentiment levels on returns. Furthermore, both Brown and Cliff (2005) as well as Hvidkjaer (2006) document that the effect of individual sentiment can have long lasting effects of several months up to two or three years. To accommodate these prior findings we estimate long-horizon return regressions of the form

$$\frac{1}{\kappa}\sum_{\kappa=1}^{k} r_{t+\kappa}^{i} = \delta_0^{i,(k)} + \delta_1^{i,(k)} sent_t^i + \Psi_t^i \gamma^{i,(k)\prime} + \xi_{t+1 \mapsto t+k}^{i,(k)} \quad (2.2)$$

with the average k-period return[18] for country i as dependent variable and several predictors on the right-hand side. These predictors include consumer confidence as a proxy for individual sentiment (*sent*) and additional macro variables which are

[18] As in Hong et al. (2007) we use raw returns since reliable data on risk-free rates is hard to obtain outside the U.S.

collected in matrix Ψ. Specifically, we include annual CPI inflation, the annual percentage change in industrial production, the annual change in employment and the term spread in Ψ to net out effects of macro risk factors on returns. The component of consumer confidence that is not attributable to these macro factors yields our proxy for individual sentiment.[19] As usual, we employ known up-to-week *t* information to forecast mean excess returns beginning in month *t+1* only. Furthermore, to facilitate comparisons of the sentiment-return relation between countries we standardize all variables used in (2.2).

A well known problem with regressions of the form in (2.2) is, that standard econometric inference, even when accounting for the serial correlation in the standard errors induced by overlapping horizons, most probably yields biased estimates of the slope coefficients. Several authors (see Stambaugh, 1999, Valkanov, 2003, or Ferson et al., 2003) have documented this problem, which is caused by highly persistent regressors. In this case OLS estimation results are still consistent but suffer more than likely from severe biases in finite samples although all regressors are predetermined. For simple regressions with only one predictor it can be shown analytically that the bias in coefficient point estimates increases in the degree of persistence of the regressor (see Stambaugh, 1999). As we show in Table 2.1 the consumer confidence indexes employed are highly persistent.[20] As noted above, a further complication arises from the overlapping of the means of returns, which induces a moving average structure of order (k-1) to the error terms.

There are several, necessarily imperfect ways to handle this problem. Several authors (e.g. Brown and Cliff, 2005) rely on some form of simulation procedure. Another way is to use auxiliary regressions (Amihud and Hurvich, 2004).[21] In order to establish comparability with the results of Brown and Cliff (2005) which is closest to our approach of detecting an influence of past sentiment on aggregate market returns, we exactly follow their method which consists of simulating small sample p-values and test statistics for the coefficient estimates of each country's return regression separately.

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[19] Baker and Wurgler (2006) and Lemmon and Portniaguina (2006) also net out macro risk factors from their sentiment proxy to obtain an explanatory variable that is unrelated to fundamental risk factors.

[20] Brown and Cliff (2005) also find individual sentiment from direct investor surveys in the U.S. to be highly correlated over time. Therefore, the high degree of persistence is not special to the consumer confidence indices employed here.

[21] Campbell and Yogo (2006) provide a method for efficient tests of stock return predictability in the presence of near unit-root regressors. However, their method does not extend directly to multiple regressors and multi-period forecasts.

A detailed description of the method employed can be found in Appendix 1 of Brown and Cliff (2005). Here we only note the main steps for completeness. First, we estimate a VAR(1) that consists of all variables used, i.e. returns, consumer confidence and all macro factors for country *i*. The residuals are stored. Next we simulate artificial time series for all endogenous variables by bootstrapping from the residuals obtained in the first step. Importantly, to simulate time series under the null of no influence of sentiment in returns, we turn off this influence by setting the coefficient of lagged sentiment on returns in the VAR coefficient matrix to zero. In this fashion, we simulate 10,000 artificial time series for all variables *without* return predictability. With these series in hand, we estimate equation (2.2) 10,000 times on the new time series to obtain the bootstrapped distribution of slope coefficients. This distribution can then be used to measure the bias in coefficient estimates $\hat{\delta}_1$ introduced by the persistence in regressors and to obtain bootstrap p-values for the significance of the estimated coefficients. We report bias-adjusted coefficient estimates and bootstrap p-values throughout the rest of this section.

2.4.2 Results

Results of this estimation procedure are shown in **Table 2.3** for aggregate stock market returns. We provide coefficient estimates for forecasting horizons of one, three, six, twelve and 24 months to document the time pattern of the sentiment-return relation. As is evident, the estimated coefficients for the impact of sentiment on expected returns are negative for the majority of markets and horizons. This is in line with earlier findings for the U.S.

The estimated coefficients are directly comparable across countries since we have standardized both dependent and independent variables for each country. As can be inferred from the magnitude of coefficients, the impact of sentiment on returns varies quite a lot across markets. For example, for the U.S. a two standard deviation shock of sentiment leads to a decline in returns in the following month of only 0.12%.[22] The same calculations for e.g. Austria, Italy and Japan give numbers of about 0.25%, 0.50% and 1.20%, respectively. Therefore, the effect of sentiment waves on returns is not

[22] This effect is smaller than the effect reported in Brown and Cliff (2005) where a two standard deviation shock leads to a monthly decline of roughly 0.29% over three years (calculated from Table 5 of their paper). However, the paper uses a different sentiment proxy and different sample period so that direct comparisons may be misleading.

overly strong for the U.S. but much stronger for several countries in Europe and, surprisingly, for Japan.

Looking at another dimension of predictability, the incremental adj. R^2s, i.e. the differences between the adj. R^2 when including macro factors and consumer sentiment jointly and the adj. R^2 when including macro factors only, are of economic significance for the same set of the markets. For example, the adj. R^2 for Italy rises from 0% to 3% on a monthly horizon and from 5% to 18% on a 6 months horizon when adding lagged sentiment to the predictive regression. It seems that sentiment has quite some explanatory power in these markets.

Overall, statistical significance is only obtained for 10 of 18 countries, indicating that the negative effect of sentiment on stock returns does not seem to be a universal phenomenon across countries. We will investigate the nature of this cross-sectional pattern in section 2.5.

Looking at the forecasting performance at different horizons more closely one can see that statistical significance of the sentiment predictor does not seem to uniformly increase with horizon. It is often argued that long-horizon regressions with nearly integrated regressors spuriously generate significant results at increasing horizons (cf. Hong et al. (2007), p. 17 for a discussion). If there was a bias in our results not eliminated by the bootstrapping procedure that mechanically generated significant results over longer horizons, one would expect to see exactly such a result. Yet, this is not the case here. In fact, there are several countries, e.g. Japan, Spain or Switzerland, where sentiment predicts aggregate market returns only at short horizons but not at longer horizons. Furthermore, the estimated coefficients tend to decrease in horizons and do not increase. Both findings are comforting and suggest that our regressions are informative and not just due to estimation biases.

Table 2.4 (**Table 2.5**) show estimated coefficients for the relation between sentiment and value (growth) stocks internationally. Baker and Wurgler (2006) argue that the sentiment-return relation should be notably strong for firms that are hard to value and hard to arbitrage and find that both value and glamour stocks are prone to the influence of sentiment whereas Lemmon and Portniaguina (2006) find slightly weaker evidence for sentiment effects on these groups of stocks and document an effect mainly for value stocks. Our results for value and glamour stocks are by and large consistent with Baker and Wurgler's findings. Almost all stock markets that are statistically significantly affected by lagged sentiment also show a statistically significant effect of sentiment on value and growth stocks. However, these effects are on average only marginally larger than for the aggregate market. Continuing with the countries mentioned above, we find an impact of a two standard deviation sentiment movement on value (growth) stocks for the U.S. of 0.11% (0.13%), for Austria of about 0.40% (0.30%), for Japan of 1.37% (1.25%) and for of Italy of roughly 0.7% (0.45%).

Finally, we note that our results are also in line with the scant earlier evidence for other countries. As in our results, Jackson (2003) finds no significant evidence for return reversals in Australia while Schmeling (2006) finds evidence for a significant impact of individual sentiment on aggregate market returns in Germany.

2.4.3 Some perspective on robustness

A natural objection might be that consumer confidence indices are not collected in a consistent way across countries which leads to spurious findings for some countries but to no significant results for others. This argument clearly overlooks, that we obtain sentiment measures for the 11 European countries from a single source, so that sentiment in these countries is collected in exactly the same way and at the same time. However, the results on the sentiment-return relation vary markedly among the 11 European countries. This cannot be attributed to differences in the survey design.

A second objection might be that econometric results based on predictors with such a hefty autocorrelation as documented in Table 2.1 are unreliable so that results seem to be spurious. However, several confidence indexes compiled from the same data collector (DG ECFIN) are available for the European countries. These other confidence indices share almost the same degree of serial correlation and describe measures of economic expectations too, such as the "DG ECFIN economic confidence index" that analyzes economic expectations for several groups including consumers, manufacturers etc.. Employing these sentiment indices as predictors in regression (2.2) produces hardly any significant results.[23] The estimated coefficient is actually positive for most countries. Therefore, the high degree of persistence in the confidence indices does not seem to drive the results. These are obtained by consumer sentiment only, as it is predicted by the notion that irrational individuals drive markets above or below fundamentally warranted levels.

[23] Results are not reported to conserve space but are available from the authors upon request.

As a third test, we estimate the specification (2.2) on sub samples and with a varying number of macro factors included. We do not report the results for brevity but note that our conclusions are qualitatively unchanged.

Finally, we look at the correlation of unexpected returns and sentiment innovations as suggested by Pastor and Stambaugh (2006). The idea in the sentiment-return context here is that in a predictive regression of the form

$$r_{t+1}^{i} = \delta_0^{i} + \delta_1^{i}sent_t^{i} + \Upsilon_t^{i}\gamma^{i\prime} + \xi_{t+1}^{i} \tag{2.3}$$

$$sent_{t+1}^{i} = \alpha_0^{i} + \alpha_1^{i}sent_t^{i} + \eta_{t+1}^{i} \tag{2.4}$$

a plausible result would be that the innovations ξ_t^i , i.e. the unexpected return, and η_t^i, i.e. the innovation in noise trader optimism, are positively correlated since it is presumably a wave of unexpected optimism that boosts prices. Therefore, under a behavioral story one would expect to see a positive correlation of ξ_t^i and η_t^i whereas one would most probably expect to see a negative correlation under a rational story (see the discussion in Pastor and Stambaugh, 2006) where consumer confidence is informative about discount factors.

We report the correlation of ξ_t^i with η_t^i for all countries *i* in **Table 2.6**. It is obvious that the typical correlation of unexpected returns with sentiment shocks is positive. Furthermore, countries that show a significant relation between returns and sentiment tend to have higher correlation coefficients of the two shocks. This is in line with the story that irrational noise trader sentiment drives price away from fundamentally warranted levels.

2.5 Cross-sectional analyses

2.5.1 Possible determinants of cross-sectional variation in the sentiment-return relationship

In this section we discuss possible explanatory variables for the cross-sectional analysis of the sentiment-return relation for our 18 countries. We start by identifying behavioral factors based on the analysis by Chui, Titman and Wei (2005) and then move on to some often used proxies for market efficiency that might drive cross-country results.

Behavioral factors

The behavioral explanation of the sentiment-return relation says that individuals herd and overreact. Therefore, our findings could be explained by systematic cross-country differences in herd-like overreaction. As noted in the introduction, Chui, Titman and Wei (2005) suggest that differences in collectivistic behavior might be a driver of the tendency of investors to herd. Therefore, we employ a measure of collectivism constructed by Hofstede (2001) which serves to quantify the degree to which people in different countries are programmed to act in groups and not as individuals.[24]

However, herd-like behavior, or correlated behavior across individuals, is not the only ingredient to this behavioral story. Individuals also have to overreact to create the negative relation between sentiment and returns. This point is crucial and is suggested by the findings of Jackson (2003). Jackson (2003) shows with broker level trading data for individual investors in Australia, that there is considerable systematic trading by individuals, i.e. trading decision are correlated and do not wash out on an aggregate level. However, he does not find evidence for short-run return reversals after waves of correlated behavior. Therefore, any empirical test of the behavioral story must take into account both dimensions, herding and overreaction.

We employ a second index by Hofstede to capture the likely degree of overreaction across countries. The uncertainty avoidance index (UAI) measures the degree to which a culture programs its members to react to unusual and novel situations. While this is not directly addressed in our analysis here, Hofstede documents that people in more uncertainty avoiding countries act and react more emotional compared to countries with low levels of uncertainty avoidance. People in the latter countries act more contemplative and thoughtful. Therefore, we employ the uncertainty avoidance index as a rough proxy for the tendency of individuals to overreact. Furthermore, it is known that UAI is correlated with the collectivism index since the UAI also captures cross-country differences in the tendency of people to follow the same sets of rules and thus behave in the same manner. This is correlated with collectivism and in our sample the correlation between collectivism and uncertainty avoidance indeed is about 0.50. Therefore, higher levels of the uncertainty avoidance index (UAI) should indicate both a tendency towards more overreaction-like behavior and herd behavior.

[24] Chui, Titman and Wei (2005) use the same index to measure individualism which is the original index by Hofstede (2001) where higher values mean higher individualism. We just pre-multiply index values by -1 to obtain our measure for collectivism.

We are well aware of the data-mining problem involved here. While the index on collectivism has proved powerful in the paper by Chui, Titman and Wei (2005) and is thus less affected from this problem, we are not aware of a finance paper that uses the UAI of Hofstede. Therefore, we will carefully investigate whether this measure has its predicted effect on the sentiment-return relationship individually and in combination with other factors.

Market integrity

As a second set of explanatory variables we use proxies for what Chui, Titman and Wei (2005) call "stock market integrity". The idea behind these variables is that markets with higher institutional quality should have a more developed flow of information and are consequently more efficient. In order to allow for a direct comparison with Chui, Titman and Wei (2005) we include the same variables as in their study. However, we collect additional variables related to the informational efficiency of a country which are detailed and grouped into “other factors” below.

The market integrity variables include a dummy for the legal origin of a country (DL, the dummy equals one when a country is common law and zero for civil law), the index of anti-director rights (a higher index means better investor protection), the corruption perception index (Cpix, higher levels mean less corruption) and accounting standards (acct, a higher index means better accounting standards). These variables are taken from La Porta et al. (1998). Additionaly, we follow Chui, Titman and Wei (2005) and include the risk of earnings managements index (emgt., a higher value means a higher risk of earnings management in that country).

Other factors

As highlighted above, superior institutional characteristics should alleviate the impact of noise traders on markets. The market integrity factors are not the only proxies which might intuitively be related to the sentiment-return relation. We consider additional factors, most of which have been employed in earlier studies, and document these below.

As proxies for the information environment we employ the following variables from Chang, Khanna and Palepu (2000): (average) number of analysts, the average forecast error, and the forecast dispersion per stock. These variables are included since it might be expected that a higher number and forecast quality of analysts leaves less room for systematic misevaluations and reduces limits to arbitrage, respectively. Griffin, Nardari and Stulz (2007) also use these variables as explanatory variables to single out rational vs. behavioral factors.

As another potentially important determinant we include in the analysis is the share of institutional investors in a country. A larger market share of institutions should benefit market efficiency since it is implicitly assumed that institutions fulfill the role of informed investors or rational arbitrageurs due to their size and relative sophistication (compared to irrational individual investors). We would therefore expect to see a lower impact of sentiment on returns in countries with a large market share of institutions. Data come from the OECD.

Also, we collect data on turnover and data on market capitalization in relation to GDP as two proxies for the activity and size (maturity) of a country, respectively. These variables capture the conjecture that more liquid and larger markets leave less room for misevaluation due to overreaction of individual traders. The turnover data is the average turnover in relation to market capitalization from Griffin, Nardari and Stulz (2007) whereas the ratio of market capitalization to GDP is from the World Bank data base.

We furthermore employ a dummy variable that equals one if short-selling is practiced in a respective country and zero otherwise. Short-selling might allow rational investors to better arbitrage overvaluations and could therefore lower the impact of sentiment on returns. The short-selling dummy (SSD) is constructed from the paper by Bris, Goetzmann and Zhu (2007) who show that short-selling benefits market efficiency and price discovery.

Finally, we employ World Bank data on education since it may be reasonably assumed that countries with a superior level of education accommodate fewer irrational noise traders. We take the percentage of a country’s population that enjoyed enrolment in tertiary education as our proxy for education.

2.5.2 Results

To investigate the potential determinants of the cross-sectional variation in sentiment-return relation we start by running regressions of the following form

$$\hat{\delta}_1^{i,(k)} = \beta_0 + \beta_1{}' x_i + \vartheta_i \qquad (2.5)$$

where $\hat{\delta}_1^{i,(k)}$ is the estimated impact of individual sentiment on average returns over *k* months and x_i is a scalar or column vector of characteristics (detailed in the previous subsection) for country *i* and ϑ_i is an error term. We will generally work with the direct impact of this month's sentiment on next month's return, i.e. *k*=1, but note, that results reported in the following are very similar for other horizons *k*>1. For future interpretation of results we note, that lower values of the dependent variable $\hat{\delta}_1^i$ imply a stronger effect of sentiment on returns.

Table 2.7 shows results for simple OLS regressions with White standard errors. As for the behavioral factors, both higher levels of collectivism and higher levels of the UAI (recall that higher levels of this index mean more emotional and blindfolded actions by people in that country) are significantly related to a stronger sentiment-return relation, i.e. the coefficients are negative. This is well in line with the predictions of Chui, Titman and Wei (2005) that collectivism boosts herd like overreaction and our discussion in the preceding subsection about the influence of UAI on the link between noise trader sentiment and returns. The adj. R^2s of roughly 23% (collectivism) and 36% (UAI) are quite large and suggest that cultural factors might play a key role for the occurrence of market anomalies across countries as suggested by Chui, Titman and Wei (2005).

From the group of variables belonging to the market efficiency proxies, only the Cpix and the index on earnings management play a significant role with similarly high adj. R^2s of 30% for the Cpix and 17% for the earnings management index.

Additional variables often have the expected sign, e.g. larger forecast errors, larger forecast dispersion, less institutional investors as well as higher turnover and a larger size of the market as measured by market cap. to GDP that are associated with larger effects of return on sentiment. However, all of these additional variables fail to be significant or to provide an acceptable explanatory power in terms of their adj. R^2 except for the education variable. Better education significantly reduces the effect of sentiment on returns as one would intuitively expect with an adjusted R^2 of roughly 16% which comes close to the explanatory power of the behavioral factors.

A natural question to ask is whether the cultural factors are more powerful in explaining the cross-section compared to the market efficiency proxies. Since our sample of 18 countries is too small to allow for a large set of regressors we proceed in the following way. We use the first principal component of the collectivism index and the UAI of all 18 countries as a culture proxy

$$\text{PC culture} = 0.71 \cdot \text{collectivism} + 0.71 \cdot \text{UAI} \tag{2.6}$$

which captures 76% of the covariance of the two series. Both loadings are positive, so we would expect to see a larger impact of past sentiment on returns in countries with a high value of this first principal component. For the market efficiency proxy we obtain the first principal component of the market integrity factors[25] for all 18 countries

$$\text{PC market efficiency} = \text{-0.58} \cdot \text{Acct-0.47} \cdot \text{Anti-0.32} \cdot \text{Cpix+0.58} \cdot \text{Emgt} \tag{2.7}$$

which captures about 65% of the total covariation between the four series. Due to the scaling of the involved indices, a higher value of the principal component indicates worse institutions. Running regression (2.5) with both principal components as explanatory variables yields the following result:

$$\underset{}{\hat{\delta}_1^i} = \underset{(0.02)}{-0.014} + \underset{(0.04)}{0.013}\,\text{PC culture}_i - \underset{(0.99)}{0.00}\,\text{PC market efficiency}_i \;, \; \bar{R}^2 = 0.41 \tag{2.8}$$

with p-values in parentheses. Evidently, as in Chui, Titman and Wei (2005), the cultural factors heavily dominate the market integrity variables in terms of cross-country explanatory power.

As a next step we follow Chui, Titman and Wei (2005) and conduct a bootstrap analysis which is build on randomly assigning values of an explanatory variable to the dependent variable of country *i*. We use 10,000 simulations for each country and explanatory variable and compute the slope coefficient each time. As before, we denote the estimated slope coefficient from equation (2.5) as $\hat{\beta}$, the average of the 10,000 bootstrap estimates of the slope coefficient as $\bar{\hat{\beta}}$ and the standard deviation of these slope coefficients by $\sigma\left(\hat{\beta}\right)$. The bootstrap t-values of a slope coefficient can then be computed via

$$t_{\text{boot}} = \left(\hat{\beta} - \bar{\hat{\beta}}\right)^2 / \sigma\left(\hat{\beta}\right). \tag{2.9}$$

[25] We only use the 4 non-dummy variables used by CWT since they seem to have most explanatory power as documented in Table 7. Other combinations yield qualitatively identical results.

The results of this procedure are shown in **Table 2.8** and are confirmative of the conclusions drawn from Table 2.7. The behavioral factors, i.e. collectivism and the overreaction proxy (UAI) are statistically significant and so is the first principal component of the two cultural dimensions shown in equation (2.7). Likewise, the only other significant variables are the Cpix and Emgt and education as before.

As a final robustness check, we employ a binary logit model where the dependent variable equals one if the coefficient of sentiment in regression equation (2.2) is significant, i.e. when there is a statistically significant effect of sentiment on returns, and zero otherwise. We employ the same explanatory variables on the right hand side. Results are presented in **Table 2.9** and show that the cultural and market integrity factors also do a reasonable job in explaining whether a certain country has a significant sentiment-return relationship or not. Note that education is not significant in this setting.

2.6 Conclusions

We investigate the relation between investor sentiment and future stock returns for 18 industrialized countries in the world and find, that sentiment plays a role in only one half of the countries in our sample. As a pure out of sample test of the sentiment-return relation uncovered for the U.S., this is not very compelling evidence that noise traders move stock prices above or below fundamentally warranted levels. This is true for aggregate market returns as well as for value and growth stocks. The story seems to be more complex than this.

In order to investigate this issue, we look at possible determinants of the strength of the relation between sentiment and returns and find that the influence of noise traders on markets varies cross-sectional in a way that is economically intuitive. The impact of sentiment on returns is higher for countries that are culturally more prone to herd-like investment behavior as hypothesized by Chui, Titman and Wei (2005) and for countries that have less efficient regulatory institutions or less market integrity.

All in all, the findings do not support the notion that irrational noise traders move markets uniformly across countries. Rather than that, institutional quality and more trading culture are strong determinants of the sentiment-return relation.

Table 2.1 Descriptive statistics

This table shows descriptive statistics for all countries used in the analysis. In particular, the table shows the start month of the sample (all series end in December 2005) and the source of the data. Furthermore, it shows means (μ) and standard deviations (σ) for the market return (Market), returns of value stocks (High B/M) and growth stocks (Low B/M). Finally, the last three columns show the mean, standard deviation and first order autocorrelation for the consumer confidence indices employed.

Country	Label	Start	Source	Market		High B/M		Low B/M		Consumer Confidence		
				μ	σ	μ	σ	μ	σ	μ	σ	ρ_{-1}
Australia	ATRL	1985 M1	Datastream	1.24	4.86	1.55	5.11	1.06	5.55	100.59	12.66	0.92
Austria	ATR	1996 M1	DG ECFIN	1.40	4.67	1.91	6.45	0.80	4.54	-1.36	6.41	0.91
Belgium	BEL	1985 M1	DG ECFIN	1.29	5.09	1.83	6.69	1.13	5.30	-7.00	9.53	0.95
Denmark	DEN	1989 M1	DG ECFIN	1.06	5.13	1.24	5.93	1.03	6.10	5.38	8.36	0.95
Finland	FIN	1995 M11	DG ECFIN	1.46	8.97	1.54	7.16	1.69	10.90	14.90	3.84	0.89
France	FRA	1985 M1	DG ECFIN	1.23	5.89	1.54	6.99	1.10	5.83	-18.60	8.49	0.94
Germany	GER	1986 M1	DG ECFIN	0.79	6.16	1.42	6.65	0.69	6.93	-8.98	8.79	0.97
Ireland	IRE	1991 M1	DG ECFIN	1.33	5.26	1.87	7.66	1.05	6.33	-3.87	13.52	0.97
Italy	ITA	1985 M1	DG ECFIN	1.29	7.09	1.25	8.14	1.26	7.20	-12.78	7.06	0.93
Japan	JAP	1985 M1	Datastream	0.49	5.80	1.11	6.70	0.20	6.40	43.26	4.62	0.97
Netherlands	NET	1985 M1	DG ECFIN	1.11	5.07	1.62	7.15	1.04	4.90	4.02	11.68	0.97
New Zealand	NEWZ	1989 M1	Datastream	0.64	5.30	-0.35	8.51	0.80	5.95	112.95	12.00	0.99
Norway	NOR	1992 M9	Datastream	1.44	5.86	2.05	9.57	1.27	5.97	20.06	13.38	0.97
Spain	SPA	1988 M1	DG ECFIN	1.20	5.75	1.74	5.69	0.77	6.28	-10.34	8.96	0.95
Sweden	SWE	1995 M9	DG ECFIN	1.29	6.69	1.65	6.53	1.10	8.35	7.39	7.21	0.94
Switzerland	SWI	1985 M1	Datastream	1.08	4.97	1.31	6.82	0.97	4.84	-10.83	21.66	0.99
United Kingdom	UK	1985 M1	DG ECFIN	1.07	4.64	1.25	5.48	0.99	4.75	-8.25	7.81	0.93
United States	US	1985 M1	Datastream	1.08	4.43	1.23	4.10	1.09	4.88	95.29	12.90	0.84

Table 2.2 Correlations of international consumer confidence indices
This table shows correlation coefficients of consumer confidence indices across countries. The upper right triangular corresponds to consumer confidence levels whereas the lower left triangular shows correlations for changes in consumer confidence.

	ATRL	ATR	BEL	DEN	FIN	FRA	GER	IRE	ITA	JAP	NET	NEWZ	NOR	ESP	SWE	SWI	UK	US
ATRL		-0.04	-0.02	0.66	-0.26	0.15	-0.30	0.43	0.03	-0.41	-0.02	0.76	0.33	0.20	-0.11	-0.05	0.48	0.31
ATR	0.22		0.75	-0.07	0.27	0.77	0.71	0.17	0.42	-0.29	0.17	-0.14	-0.41	0.33	0.76	0.72	-0.07	0.13
BEL	0.02	0.14		0.09	0.52	0.83	0.65	0.58	0.61	-0.02	0.55	-0.23	0.06	0.73	0.80	0.50	0.35	0.35
DEN	-0.01	-0.07	0.08		0.32	0.27	-0.10	0.66	0.27	-0.37	0.26	0.55	0.73	0.34	0.13	0.07	0.62	0.24
FIN	0.06	0.12	0.18	0.00		0.52	0.43	0.77	0.07	0.15	0.75	-0.47	0.26	0.63	0.61	0.37	0.54	0.61
FRA	0.04	0.11	0.30	0.12	0.05		0.63	0.67	0.54	-0.10	0.55	0.08	0.06	0.66	0.83	0.59	0.34	0.36
GER	-0.02	0.19	0.11	-0.09	0.11	0.03		0.48	0.67	0.25	0.55	-0.31	-0.01	0.62	0.70	0.83	-0.01	0.26
IRE	0.03	0.17	0.15	0.12	0.10	0.16	0.07		0.50	-0.17	0.82	0.18	0.44	0.82	0.47	0.71	0.74	0.66
ITA	0.06	0.22	0.17	0.24	0.08	0.03	-0.01	0.09		-0.03	0.56	-0.05	0.27	0.73	0.24	0.60	0.34	0.34
JAP	0.08	-0.05	0.20	0.01	0.08	0.12	0.00	0.05	0.06		0.01	-0.38	0.50	-0.06	-0.10	0.22	-0.29	0.02
NET	0.03	0.16	0.24	0.25	0.13	0.17	0.11	0.24	0.19	0.04		-0.17	0.33	0.76	0.44	0.52	0.35	0.60
NEWZ	0.11	-0.05	0.01	-0.06	0.05	0.12	0.02	0.00	-0.03	-0.03	-0.05		0.32	-0.08	-0.38	-0.07	0.33	0.05
NOR	-0.01	0.16	0.07	0.04	0.19	-0.01	0.01	0.09	0.02	0.11	0.17	0.13		0.33	-0.19	0.11	0.49	0.28
SPA	-0.02	-0.02	0.13	0.11	0.07	0.26	0.15	0.03	0.25	0.02	0.16	-0.05	0.05		0.55	0.70	0.60	0.57
SWE	0.16	0.27	0.13	0.13	0.25	0.19	0.18	0.04	0.17	0.14	0.14	-0.06	0.13	0.02		0.69	0.18	0.45
SWI	-0.02	0.00	0.14	-0.03	0.10	0.12	0.23	0.11	0.12	0.03	0.14	-0.04	0.16	0.09	0.06		0.22	0.44
UK	0.12	0.08	0.19	0.21	0.09	0.00	0.00	0.24	0.21	0.00	0.08	0.09	0.14	0.22	0.18	-0.07		0.46
US	0.20	0.14	0.14	0.16	0.05	0.09	-0.05	0.11	0.09	0.00	0.17	-0.01	-0.10	0.05	0.17	0.02	0.13	

Table 2.3 Predictive regression results: aggregate stock market
This table shows predictive regression results for the model specified in (2.2) with aggregate market returns as dependent variables. $\Delta\overline{R}^2$ denotes the incremental adj. R^2 when sentiment is included in the regression specification. Reported coefficient estimates are bias adjusted and bootstrap p-values are shown. Stars refer to the level of significance: *** 1%, ** 5%, * 10%.

	1 month		3 months		6 months		12 months		24 months	
	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$
ATRL	0.001	-0.01	0.000	0.00	0.000	0.01	0.001	0.00	0.002	-0.01
	(0.96)	0.00	(0.74)	0.00	(0.80)	0.00	(0.95)	0.00	(0.79)	0.00
ATR	-0.028	0.00	-0.031	0.08	-0.038	0.28	-0.023	0.22	-0.005	0.36
	**(0.03)	0.02	**(0.03)	0.07	**(0.01)	0.22	**(0.02)	0.17	(0.54)	0.01
BEL	-0.021	0.07	-0.021	0.12	-0.021	0.23	-0.020	0.42	-0.018	0.54
	***(0.00)	0.04	***(0.00)	0.10	***(0.00)	0.21	***(0.00)	0.38	***(0.01)	0.54
DEN	0.008	0.03	0.005	0.00	0.003	0.00	0.002	0.03	0.005	0.04
	(0.56)	0.00	(0.76)	0.00	(0.94)	0.00	(1.00)	-0.01	(0.75)	0.01
FIN	0.020	0.01	0.032	0.10	0.039	0.24	0.015	0.42	0.007	0.50
	(0.65)	-0.01	(0.42)	0.01	(0.20)	0.04	(0.37)	0.01	(0.76)	0.00
FRA	-0.018	0.00	-0.012	0.01	-0.007	0.02	-0.007	0.06	-0.015	0.23
	*(0.09)	0.01	(0.21)	0.01	(0.37)	0.01	(0.35)	0.02	**(0.01)	0.16
GER	-0.015	0.03	-0.018	0.04	-0.019	0.10	-0.017	0.17	-0.015	0.30
	**(0.05)	0.01	**(0.02)	0.05	**(0.02)	0.11	*(0.05)	0.18	*(0.06)	0.27
IRE	0.003	0.04	0.002	0.07	0.001	0.14	0.000	0.20	-0.004	0.41
	(0.78)	0.00	(0.97)	-0.01	(0.99)	-0.01	(0.82)	0.00	(0.22)	0.08
ITA	-0.035	0.03	-0.033	0.10	-0.033	0.18	-0.028	0.24	-0.009	0.09
	***(0.00)	0.03	***(0.00)	0.08	***(0.00)	0.13	***(0.01)	0.17	(0.38)	0.03
JAP	-0.102	0.06	-0.075	0.11	-0.057	0.16	-0.029	0.09	-0.019	0.06
	***(0.00)	0.05	***(0.00)	0.07	**(0.02)	0.07	(0.21)	0.04	(0.22)	0.03
NET	0.002	0.03	0.002	0.03	0.001	0.05	0.000	0.08	-0.003	0.12
	(0.96)	0.00	(0.95)	0.00	(0.86)	0.00	(0.75)	0.00	(0.48)	0.05
NEWZ	0.009	0.06	0.006	0.13	0.004	0.09	0.002	0.21	-0.001	0.19
	(0.44)	0.00	(0.66)	0.00	(0.86)	0.00	(0.89)	0.00	(0.68)	0.02
NOR	-0.005	-0.01	-0.003	0.00	-0.003	0.04	-0.005	0.14	-0.003	0.28
	*(0.09)	0.01	(0.24)	0.02	(0.25)	0.04	(0.14)	0.11	*(0.09)	0.14
SPA	-0.017	0.09	-0.015	0.13	-0.015	0.15	-0.013	0.20	-0.012	0.18
	*(0.06)	0.01	**(0.05)	0.04	*(0.07)	0.08	(0.21)	0.12	(0.30)	0.16
SWE	-0.002	0.04	-0.008	0.10	-0.009	0.21	-0.016	0.40	-0.011	0.45
	(0.77)	-0.01	(0.53)	0.00	(0.52)	0.01	*(0.09)	0.06	(0.32)	0.05
SWI	-0.020	0.04	-0.019	0.14	-0.013	0.21	-0.009	0.37	-0.010	0.48
	***(0.01)	0.03	**(0.03)	0.07	(0.11)	0.06	(0.17)	0.07	(0.15)	0.16
UK	-0.006	0.00	-0.007	0.02	-0.003	0.08	-0.004	0.15	-0.004	0.20
	(0.31)	0.00	(0.28)	0.01	(0.50)	0.01	(0.40)	0.03	(0.36)	0.04
US	-0.013	0.02	-0.014	0.10	-0.009	0.13	-0.005	0.17	-0.004	0.12
	**(0.02)	0.03	***(0.01)	0.09	*(0.07)	0.09	(0.20)	0.07	(0.29)	0.08

Table 2.4 Predictive regression results: value stocks
This table shows predictive regression results for the model specified in (2.2) with returns of value stocks as dependent variables. $\Delta\overline{R}^2$ denotes the incremental adj. R^2 when sentiment is included in the regression specification. Reported coefficient estimates are bias adjusted and bootstrap p-values are shown. Stars refer to the level of significance: *** 1%, ** 5%, * 10%.

	1 month		3 months		6 months		12 months		24 months	
	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$
ATRL	-0.001	-0.01	-0.003	0.00	-0.003	0.03	-0.002	0.14	-0.002	0.14
	(0.65)	0.00	(0.45)	0.00	(0.50)	0.01	(0.49)	0.02	(0.46)	0.03
ATR	-0.030	0.00	-0.030	0.04	-0.031	0.14	-0.022	0.24	-0.010	0.33
	**(0.04)	0.02	*(0.06)	0.06	**(0.02)	0.16	**(0.01)	0.23	**(0.04)	0.10
BEL	-0.013	0.04	-0.013	0.05	-0.011	0.08	-0.009	0.13	-0.007	0.18
	**(0.04)	0.01	**(0.02)	0.04	**(0.03)	0.08	*(0.06)	0.14	(0.16)	0.19
DEN	0.011	0.01	0.011	0.00	0.008	-0.01	0.008	0.01	0.007	0.08
	(0.37)	0.00	(0.35)	0.01	(0.61)	0.01	(0.59)	0.02	(0.54)	0.04
FIN	-0.023	0.00	-0.014	0.03	-0.031	0.10	-0.033	0.21	-0.020	0.50
	(0.49)	0.00	(0.64)	0.00	(0.21)	0.04	**(0.03)	0.11	**(0.04)	0.24
FRA	-0.018	0.00	-0.013	0.02	-0.008	0.04	-0.008	0.10	-0.015	0.24
	*(0.10)	0.01	(0.17)	0.01	(0.26)	0.01	(0.33)	0.02	**(0.03)	0.18
GER	-0.015	0.04	-0.017	0.05	-0.018	0.09	-0.017	0.17	-0.015	0.30
	*(0.09)	0.01	**(0.05)	0.04	**(0.04)	0.09	*(0.06)	0.18	(0.11)	0.26
IRE	0.002	-0.02	0.004	-0.02	0.003	-0.02	0.004	0.06	0.004	0.18
	(0.92)	-0.01	(0.79)	0.00	(0.84)	0.00	(0.70)	0.01	(0.26)	0.06
ITA	-0.041	0.04	-0.041	0.12	-0.041	0.22	-0.038	0.33	-0.012	0.12
	***(0.00)	0.04	***(0.00)	0.11	***(0.00)	0.19	***(0.00)	0.29	(0.21)	0.05
JAP	-0.102	0.06	-0.071	0.10	-0.064	0.20	-0.049	0.24	-0.027	0.19
	***(0.00)	0.05	***(0.01)	0.07	**(0.04)	0.11	*(0.06)	0.12	*(0.10)	0.08
NET	-0.007	0.05	-0.006	0.04	-0.006	0.06	-0.005	0.12	-0.005	0.25
	(0.19)	0.01	(0.22)	0.02	(0.16)	0.04	(0.19)	0.07	(0.14)	0.18
NEWZ	0.007	0.04	0.006	0.06	0.006	0.08	0.006	0.21	0.007	0.48
	(0.34)	0.00	(0.42)	0.01	(0.46)	0.02	(0.35)	0.06	*(0.10)	0.21
NOR	-0.010	0.03	-0.009	0.10	-0.010	0.15	-0.010	0.18	-0.005	0.31
	**(0.03)	0.03	**(0.03)	0.06	*(0.07)	0.12	*(0.08)	0.19	(0.14)	0.17
SPA	-0.006	0.04	-0.006	0.09	-0.005	0.06	-0.003	0.06	-0.003	0.02
	(0.45)	0.00	(0.29)	0.00	(0.34)	0.01	(0.65)	0.01	(0.65)	0.01
SWE	-0.040	0.04	-0.037	0.14	-0.033	0.22	-0.015	0.17	-0.004	0.52
	**(0.02)	0.04	***(0.00)	0.11	***(0.00)	0.17	*(0.10)	0.08	(0.45)	0.02
SWI	-0.013	0.04	-0.014	0.14	-0.009	0.24	-0.007	0.36	-0.011	0.46
	*(0.09)	0.01	*(0.08)	0.03	(0.24)	0.03	(0.34)	0.02	(0.14)	0.14
UK	-0.009	0.01	-0.010	0.03	-0.006	0.09	-0.007	0.14	-0.006	0.11
	(0.17)	0.00	(0.19)	0.02	(0.39)	0.02	(0.27)	0.05	(0.23)	0.07
US	-0.014	0.02	-0.015	0.09	-0.009	0.13	-0.003	0.23	-0.002	0.15
	**(0.02)	0.03	***(0.01)	0.09	*(0.09)	0.08	(0.34)	0.03	(0.18)	0.06

Table 2.5 Predictive regression results: growth stocks
This table shows predictive regression results for the model specified in (2.2) with returns of growth stocks as dependent variables. $\Delta\overline{R}^2$ denotes the incremental adj. R^2 when sentiment is included in the regression specification. Reported coefficient estimates are bias adjusted and bootstrap p-values are shown. Stars refer to the level of significance: *** 1%, ** 5%, * 10%.

	1 month		3 months		6 months		12 months		24 months	
	coef./p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$	coef./ p-val	$\overline{R}^2$/ $\Delta\overline{R}^2$
ATRL	0.003	0.00	0.001	0.03	0.000	0.04	0.001	0.01	0.001	0.00
	(0.72)	0.00	(0.91)	0.00	(0.81)	0.00	(0.97)	0.00	(0.95)	0.00
ATR	-0.033	0.01	-0.036	0.11	-0.039	0.27	-0.025	0.19	-0.006	0.39
	**(0.02)	0.03	***(0.01)	0.10	***(0.01)	0.21	*(0.09)	0.13	(0.68)	0.00
BEL	-0.020	0.06	-0.022	0.14	-0.021	0.24	-0.021	0.44	-0.018	0.53
	***(0.00)	0.03	***(0.00)	0.11	***(0.00)	0.23	***(0.00)	0.41	**(0.02)	0.52
DEN	-0.001	0.03	-0.003	0.02	-0.005	0.04	-0.006	0.06	0.000	0.00
	(0.75)	0.00	(0.59)	0.00	(0.55)	0.01	(0.44)	0.02	(0.96)	-0.01
FIN	0.033	0.00	0.034	0.09	0.044	0.23	0.019	0.39	0.011	0.49
	(0.42)	0.00	(0.35)	0.01	(0.12)	0.06	(0.27)	0.01	(0.64)	0.00
FRA	-0.019	0.00	-0.011	0.00	-0.006	0.01	-0.005	0.03	-0.012	0.19
	*(0.10)	0.01	(0.27)	0.01	(0.48)	0.00	(0.50)	0.01	*(0.10)	0.09
GER	-0.014	0.04	-0.018	0.04	-0.018	0.09	-0.016	0.16	-0.016	0.33
	*(0.08)	0.01	**(0.02)	0.05	**(0.02)	0.10	*(0.07)	0.17	**(0.04)	0.31
IRE	-0.001	0.04	-0.003	0.11	-0.004	0.22	-0.004	0.25	-0.007	0.52
	(0.73)	0.00	(0.51)	0.00	(0.46)	0.01	(0.41)	0.03	(0.14)	0.15
ITA	-0.031	0.02	-0.029	0.09	-0.029	0.16	-0.024	0.21	-0.008	0.11
	***(0.00)	0.02	***(0.00)	0.06	***(0.00)	0.10	**(0.02)	0.12	(0.45)	0.02
JAP	-0.098	0.06	-0.070	0.10	-0.051	0.14	-0.020	0.07	-0.012	0.05
	***(0.00)	0.04	***(0.00)	0.06	**(0.01)	0.06	(0.32)	0.02	(0.36)	0.01
NET	-0.002	0.02	-0.001	0.02	-0.002	0.04	-0.004	0.10	-0.007	0.24
	(0.51)	0.00	(0.53)	0.00	(0.43)	0.01	(0.30)	0.04	(0.16)	0.17
NEWZ	0.008	0.06	0.005	0.18	0.003	0.20	0.001	0.38	-0.001	0.32
	(0.58)	0.00	(0.81)	0.00	(0.96)	0.00	(0.66)	0.00	(0.66)	0.03
NOR	0.000	-0.02	0.002	-0.02	0.002	-0.01	-0.002	0.07	-0.003	0.26
	(0.47)	0.00	(0.78)	-0.01	(0.79)	0.00	(0.36)	0.04	(0.19)	0.12
SPA	-0.022	0.14	-0.020	0.20	-0.020	0.27	-0.018	0.37	-0.014	0.30
	**(0.02)	0.02	**(0.01)	0.06	**(0.02)	0.14	*(0.06)	0.22	*(0.10)	0.21
SWE	0.004	0.06	-0.001	0.11	-0.002	0.21	-0.017	0.39	-0.011	0.43
	(0.99)	-0.01	(0.79)	-0.01	(0.79)	0.00	(0.19)	0.05	(0.41)	0.04
SWI	-0.023	0.05	-0.022	0.16	-0.016	0.22	-0.012	0.41	-0.012	0.59
	***(0.00)	0.04	***(0.01)	0.11	**(0.03)	0.10	*(0.06)	0.11	**(0.04)	0.20
UK	-0.002	0.00	-0.001	0.02	0.002	0.08	0.000	0.14	-0.001	0.21
	(0.59)	0.00	(0.64)	0.00	(0.96)	0.00	(0.77)	0.00	(0.65)	0.01
US	-0.013	0.02	-0.013	0.09	-0.007	0.11	-0.004	0.16	-0.004	0.16
	**(0.02)	0.03	**(0.01)	0.08	(0.13)	0.06	(0.28)	0.05	(0.38)	0.05

Table 2.6 Correlation of consumer confidence innovations and unexpected returns
This table shows correlation coefficients for unexpected returns and sentiment innovations from the predictive system in equations (2.3) and (2.4) for market returns and returns of value and growth stocks.

	market	value	growth
ATRL	0.03	0.05	0.04
ATR	0.13	0.03	0.11
BEL	0.08	0.02	0.12
DEN	0.02	0.06	0.02
FIN	0.03	-0.03	0.04
FRA	0.14	0.16	0.12
GER	0.02	0.02	0.01
IRE	0.03	0.09	0.07
ITA	0.09	0.10	0.07
JAP	0.10	0.16	0.07
NET	0.13	0.14	0.12
NEWZ	0.20	-0.02	0.22
NOR	0.15	0.10	0.13
SPA	0.16	0.07	0.17
SWE	0.15	0.15	0.11
SWI	0.02	0.05	0.02
UK	0.12	0.12	0.12
US	0.12	0.17	0.10

Table 2.7 Cross-sectional analysis of the sentiment-return relation
The table shows univariate regression results for the cross-section of countries. Each row represents a regression with the impact of consumer confidence on next month's stock return as dependent variable and the row's variable as the explanatory variable. The second column (+ / –) shows the theoretically expected effect of a respective regressor on the dependent variable. Statistically significant results (at least at the 10%-level) are in bold numbers.

		slope coef.	t-stat	$\bar{R}^2$
Behavioral factors				
Collectivism	–	-0.109	**-2.442**	0.23
Uncertainty avoidance	–	-0.077	**-3.267**	0.36
PC culture	–	-1.371	**-3.533**	0.40
Market integrity				
Legal origin		1.672	1.229	0.03
Anti-director rights	+	0.111	0.243	-0.06
Corruption perception	+	1.524	**2.907**	0.30
Accounting standards	+	0.137	1.606	0.09
Earnings management	–	-0.157	**-2.083**	0.17
Other factors				
No. of Analysts	+	-0.024	-0.282	-0.06
Forecast dispersion	–	0.675	0.068	-0.06
Forecast error	–	-4.559	-0.712	-0.03
Share inst. investors	+	2.823	0.825	-0.02
Marketcap. / GDP	+	0.006	0.473	-0.05
Turnover	+	0.189	0.180	-0.06
Short selling	+	-2.073	-1.271	0.03
Education	+	0.096	**2.071**	0.16

Table 2.8 Bootstrap analysis
This table shows results from a bootstrap analysis where values of explanatory variables are randomly permuted across countries. Specifically, each country is assigned its own value of the regressand, the impact of sentiment on returns, and the explanatory variable for each country is drawn randomly from the pool of all countries. For the first univariate regression for example, Australia is assigned the education level of Belgium, Belgium is assigned the education level of Austria and so. This procedure is repeated 10,000 times and the empirical distribution of slope coefficients is used to construct bias adjusted test statistics as indicated in the text. The second column (+ / −) shows the theoretically expected effect of a respective regressor on the dependent variable. Statistically significant results (at least at the 10%-level) are in bold numbers.

		slope coefficient $\hat{\beta}$	mean slope coefficient from bootstrap $\bar{\hat{\beta}}$	stand. dev. from bootstrap $\sigma(\bar{\hat{\beta}})$	bootstrap t-statistic $(\hat{\beta}-\bar{\hat{\beta}})/\sigma(\hat{\beta})$
Behavioral factors					
Collectivism	–	-0.109	0.000	0.051	**-2.137**
Uncertainty avoidance	–	-0.077	0.001	0.029	**-2.635**
PC culture	–	-1.371	0.002	0.499	**-2.745**
Market integrity					
Legal origin		1.672	0.006	1.383	1.209
Anti-director rights	+	0.111	-0.008	0.449	0.247
Corruption perception	+	1.524	-0.004	0.618	**2.469**
Accounting standards	+	0.137	0.001	0.090	1.517
Earnings management	–	-0.157	0.000	0.084	**-1.872**
Other factors					
No. of Analysts	+	-0.024	0.000	0.082	-0.293
Forecast dispersion	–	0.675	0.143	9.506	0.071
Forecast error	–	-4.559	0.021	6.276	-0.727
Share inst. investors	+	2.823	0.001	3.369	0.838
Marketcap. / GDP	+	0.006	0.000	0.012	0.482
Turnover	+	0.189	-0.022	1.016	0.186
Short selling	+	-2.073	0.023	1.673	-1.239
Education	+	0.096	0.000	0.050	**1.925**

Table 2.9 Probit regressions
This table shows results from univariate probit regressions where the dependent variable equals one if there is a significant sentiment-return relation for country *i* and zero otherwise. The second column (+ / −) shows the theoretically expected effect of a respective regressor on the dependent variable. Statistically significant results (at least at the 10%-level) are in bold numbers.

		slope coefficient	t-stat	Mc-Fadden's R^2
Behavioral factors				
Collectivism	+	0.051	**1.707**	0.14
Uncertainty avoidance	+	0.090	**2.026**	0.52
PC culture	+	1.023	**2.325**	0.39
Market integrity				
Legal origin		-1.344	**-1.828**	0.15
Anti-director rights	–	-0.273	-1.172	0.06
Corruption perception	–	-1.550	**-2.473**	0.45
Accounting standards	–	-0.114	**-2.019**	0.23
Earnings management	+	0.096	**2.023**	0.21
Other factors				
No. of Analysts	–	0.055	1.285	0.07
Forecast dispersion	+	6.213	1.251	0.07
Forecast error	+	5.317	1.585	0.11
Share inst. investors	–	-2.349	-1.015	0.06
Marketcap. / GDP	–	-0.002	-0.351	0.00
Turnover	–	0.495	0.928	0.04
Short selling dummy	–	0.684	0.837	0.03
Education	–	-0.023	-0.938	0.04

Chapter 3:
A prospect-theoretical interpretation of momentum returns*

3.1 Introduction

According to standard theory, returns on investment strategies might be higher than returns on holding the market portfolio if they carry a higher systematic risk. It is therefore surprising that simple momentum investment strategies seem to contradict this conventional wisdom by offering high returns that are not explained by conventional risk factors. The challenge to traditional capital market theory is particularly bold as momentum strategies are extremely simple by just buying those assets which performed best in the past reference period and selling short the worst performing assets. Thus momentum strategies do not require any fundamental understanding of asset markets and also no effort to forecast future returns. Despite this effrontery to capital market theory, the observation of highly significant momentum returns in the US stock market (Jegadeesh and Titman, 1993) was abundantly confirmed (e.g., Jegadeesh and Titman, 2001) and extended to other markets as well (Rouwenhorst, 1998). Thus, momentum returns represent a fascinating puzzle.

We contribute towards a possible understanding of high momentum returns by following the analytical perspective suggested by Benartzi and Thaler (1995). [26] We find, indeed, that risk considerations as implemented by prospect theory might be a key: the prospect utility of US stock momentum returns is not higher than that of a comparable market portfolio. Therefore, prospect theory provides a possible direction for explaining the puzzle.

We proceed as follows: Section 3.2 introduces data and the puzzling multi-factor interpretation of US stock momentum returns. Section 3.3 demonstrates the riskiness of momentum and market returns by highlighting the higher-order statistical moments.

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[26] The failure of traditional models to explain the puzzling findings has stimulated a large body of behavioral models which inter alia include Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999).

Section 3.4 consequently presents the application of prospect theory to the momentum and market strategies respectively. Section 3.5 concludes.

3.2 Data and the multi-factor interpretation of momentum returns

We use data on the US stock market from July 1963 to December 2005. This monthly data set comprises the CRSP market return, the risk free rate, the market excess return and momentum returns from NYSE-AMEX stocks. The construction of momentum returns follows the method employed in Fama and French (1996). Stocks are ranked into deciles based on their returns in the formation period over the last year. Decile portfolios are equally weighted and momentum returns are obtained by taking a long position in the stocks of the tenth decile (P10) and shorting stocks in the first decile (P1). Portfolios are rebalanced monthly and one month is skipped between the end of the formation and the beginning of the holding period. The holding period is one month.

At the core of the momentum puzzle is the fact that this strategy is self-financing and has a significantly positive mean return, which does not seem to be compensating for any kind of conventional measure of risk. Neither traditional beta-factors nor multi-factor analyses inspired by Fama and French have been successful in capturing momentum returns (see Fama and French, 1996, Grundy and Martin, 2001). Consider for example the popular Fama-French three factor model that "explains" returns by their exposure to three risk factors. A time-series regression using GMM applied to our data leads to the following result

$$\underset{}{MOM_t} = \underset{[3.05]}{1.50} - \underset{[-1.99]}{0.24\,ER_t} - \underset{[-0.13]}{0.02\,SMB_t} - \underset{[-1.17]}{0.21\,HML_t} \quad , \; R^2 \approx 1\% \tag{3.1}$$

with t-statistics in parentheses and MOM, ER, SMB and HML denoting monthly momentum returns, market returns in excess over the risk free rate and the SMB (size) and HML (leverage) factor, respectively. As can be directly inferred, a conventional momentum strategy yields risk adjusted returns of about one and a half per cent each month over the whole sample of 42 years. A similar conclusion can be drawn from using a simple one factor market model. Seen from the viewpoint of these models, momentum strategies offer a free lunch.

3.3 Comparing statistics of market and momentum returns

Linear factor models look at first and second-order (cross-)moments of return distributions. However, there is a tendency in economics and finance to consider more complex and in particular asymmetric approaches to measure risk (see e.g. Ang, Chen and Xing, 2006). Therefore, let us take a look at the return distributions of market excess[27] and momentum returns as shown in **Table 3.1** for both monthly returns and rolling 12-months returns. Unconditional average monthly returns of the momentum portfolio are about 1.29 percent p.m. and therefore somewhat lower compared to the intercept of 1.5 percent in (3.1). However, a t-test employing Newey-West standard errors yields a test statistic of 2.45 for the null of mean zero when applied to raw momentum returns. Less advantageous for the momentum strategy is the fact that both the standard deviation and the maximum one-month loss of the momentum portfolio of 55.84 percent are much higher than the same statistics of market excess returns. A further key to understanding riskiness is provided by the more negative skewness (see also Harvey and Siddique (2000) in this respect) of momentum returns and their higher kurtosis compared to market excess returns. Except for the skewness, the ordering of these statistics for the two portfolios is unchanged when using smoother 12-months returns.

The higher maximum loss as well as the third and fourth-order statistical moments of the momentum return distribution are unattractive for loss averse investors since the latter weigh losses more heavily than gains of the same size. In this setting, and holding first and second order moments fixed, an increasingly negative skewness indicates that losses occur more often and an increasingly high kurtosis indicates that extreme return realizations become more likely. Both, negative skewness and higher kurtosis are clearly unattractive for loss averse investors.

3.4 A prospect-theoretical interpretation of momentum returns

As a way to consider loss aversion in investment decisions we follow Benartzi and Thaler's (1995) approach of myopic loss aversion which includes two modifications of the traditional capital market approach. First, they substitute the traditional symmetric risk-return approach by the empirically well established prospect theory (which incorporates loss aversion) to gauge the attractiveness of portfolio return distributions. Second, they take into account the fact that evaluation horizons of risky

[27] The market excess return over the risk free rate is an appropriate benchmark for momentum returns since it can be thought of representing an investment strategy that uses short-term loans to finance the market investment. This avoids to invest own capital and thus makes it comparable to momentum returns.

investments often do not span over decades but over months (in the case of fund managers) or a year (as sometimes assumed for private investors). Loss aversion in combination with short horizons leads to myopic loss aversion, a behavior which is increasingly confirmed by recent empirical evidence (e.g. Haigh and List, 2005, or Bellemare et al., 2005). The impact of myopic loss aversion on investment behavior can be analyzed by using prospect theory. This theory provides an empirically well established approach to assess – among others – risk-return profiles of different portfolios. Moreover, the element of a reference point in prospect theory fits well with the notion of short horizons. Therefore, prospect utility seems to be a promising approach to directly compare US momentum returns with US market excess returns in terms of the investors' utility.

Regarding the exact methodology, we follow Benartzi and Thaler (1995), who evaluate stock and bond returns with a cumulative prospect utility function to find a behavioral explanation for the equity premium puzzle. The key to their analysis is the nonlinear value function, as proposed and estimated by Kahnemann and Tversky (1979) and Tversky and Kahnemann (1992) which has the following form:

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0, \end{cases} \tag{3.2}$$

where v is the value function, x denotes returns and λ is the coefficient of loss aversion, which Tversky and Kahnemann (1992) estimate to be 2.25. The estimated values for α and β are both 0.88, creating a concave shape in the domain of gains and a convex shape for the value function in the domain of losses. This procedure models agents as risk-averse for positive and risk-seeking for negative outcomes, relative to the reference point. Since the coefficient of loss aversion is larger than one, agents put more weight on losses than on gains of the same size.

The prospective utility is just the weighted sum of these values:

$$V(G) = \sum_i \pi_i v(x_i), \tag{3.3}$$

where π_i is a transformation of the probability p_i of obtaining the *i*th outcome. In cumulative prospect utility this transformation depends not only on p_i, but also on the probabilities of the other outcomes. Specifically, π_i can be computed by taking the difference of the weighted probability of obtaining an outcome at least as good as the x_i (denoted P_i) and the weighted probability of obtaining an outcome that is better than x_i (denoted P^*_i), formally

$$\pi_i = w(P_i) - w(P_i^*) \tag{3.4}$$

and the weight w is

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} , \tag{3.5}$$

with an estimated value for γ of 0.61 and 0.69 for the domains of gains and losses respectively.

To perform the comparison of momentum and market excess returns over different horizons of evaluation, we simulate the return distributions of both strategies by drawing 1,000,000 *n*-month returns (with replacement, *n* = 1, 2, …, 30) from both return series and rank them in descending order. For each of these simulated distributions, one hundred intervals of 10,000 observations are formed and the mean return for each is computed.[28] Using these returns, the prospective utility for both series and evaluation horizon is easily obtained.

In order to get more realistic results we further take into account transaction costs of the momentum strategy. These might well be substantial since the strategy demands portfolio adjustments each month and has to deal with comparatively large bid-ask spreads of small and illiquid stocks. The existing literature often employs no transaction costs (Jegadeesh and Titman, 2001) although Korajczyk and Sadka (2004) find costs of up to five percent.

Figure 3.1 plots the result of this simulation exercise for both the momentum (dashed lines) and market excess returns (solid line) for evaluation horizons ranging from one to 36 months and for transaction costs (for the momentum strategy) ranging from zero to ten percent p.a.. As can be expected, the lowest dashed line represents the cumulative prospective utility of the momentum strategy when transaction costs equal ten percent p.a. whereas the uppermost dashed line shows the prospective utility without transaction costs. Two implications of this figure stand out. First, similar to the results in Benartzi and Thaler (1995), all self-financing stock portfolios only yield positive utility for evaluation horizons of about one year and beyond. Investors evaluating their portfolios more often are better off avoiding the two investment strategies under consideration here.[29] Second, even for very moderate transaction costs of only one

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[28] Effectively, this procedure proposed by Benartzi and Thaler (1995) simulates the distribution of returns and calculates mean returns conditional on observing an outcome in one of the hundred percentiles of the distribution. Note also, that we implement a finer grid than Benartzi and Thaler (1995) who use only twenty intervals.

[29] In our view, the fact that momentum portfolios are rebalanced monthly does not necessarily conflict with investors employing longer evaluation horizons for at least two reasons. First, rebalancing is a purely mechanical activity that does not force investors to evaluate the

percent p.a., investors with evaluation horizons of more than two years do not prefer momentum portfolios to the self-financing market portfolio.

This is a possible explanation for the puzzling observation that momentum returns do not attract arbitrageurs who exploit this opportunity of seemingly risk free profits. The fact that prospective utility investors are loss averse prevents them from holding a momentum portfolio that has a more extreme return distribution than the comparable market portfolio. Although longer evaluation horizons tend to erase some of the skewness and kurtosis (see Table 3.1), a conventional momentum strategy does not clearly outperform the self-financing market portfolio in terms of the investors' utility over any reasonable evaluation horizon and for reasonable transaction costs.

Figure 3.2 documents further analyses in the spirit of Benartzi and Thaler (1995). Panel (A) shows cumulative prospective utilities for different portfolio allocations of the momentum strategy and the self-financing market portfolio at a 12 months evaluation horizon. The different lines correspond to transaction costs of zero to ten percent p.a. As was shown in Figure 3.1, a pure momentum strategy yields a marginal positive utility at the 12 months horizon. Adding transaction costs, this utility becomes negative immediately. However, combining the momentum strategy with the self-financing market portfolio can improve utility. This is easily explained by the apparent lack of correlation between momentum and market excess returns as indicated in equation (3.1). However, the optimal share of the momentum portfolio ranges from 24 percent to 32 percent only and imposing transaction costs of more than seven percent p.a. does not yield positive utilities anymore. This clearly reduces the possibility to arbitrage momentum strategies.

Finally, Panel (B) of 3. 2 shows the implied momentum premium investors with evaluation horizons from one to fifteen years demand for holding the momentum portfolio. Again, the figure has intuitive appeal and is similar to the results in Benartzi and Thaler (1995). Leaving transaction costs aside, short-termism of investors demands a high momentum return of almost 16 percent p.a. in order to make this strategy attractive to investors with a one year evaluation horizon. Patient investors with an evaluation horizon of e.g. 15 years only demand a premium of about four percent p.a. to compensate for the higher order moment risk associated with momentum returns.[30]

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performance of their investment strategy. Second, momentum investing can be delegated to asset managers so there is no monthly activity on behalf on the investor at all.

[30] All results are qualitatively identical when using the popular UMD momentum data (available from Kenneth French's web site) over a period of 80 years or data for a strategy of a six months formation and six months holding period as applied in Chordia and Shivakumar (2002).

3.5 Conclusion

The interpretation of US stock momentum returns over 42 years from the viewpoint of prospect theory suggests that loss adverse investors may be (partially) compensated for the higher probability of extreme losses and risk in higher order moments over reasonable evaluation horizons. Thus prospect theory seems to provide a fruitful access to analyze financial risks, which was shown earlier regarding portfolio choice (Berkelaar et al., 2004), the equity premium puzzle (Benartzi and Thaler, 1995 or Barberis et al., 2001) and is shown here regarding the puzzle of high momentum returns.

Table 3.1 Descriptive statistics of momentum and market excess returns
MOM and ER denote momentum returns and the market excess return over the risk free rate, respectively. 12-month returns are obtained by chaining monthly returns. The sample period is 1963:07 to 2005:12.

	Monthly returns (in %)		12-months returns (in %)	
	MOM	ER	MOM	ER
Mean	1.29	0.47	17.01	5.63
Median	1.84	0.76	13.98	8.13
Maximum gain	31.91	16.05	204.77	54.17
Maximum loss	-55.84	-23.13	-70.38	-45.76
Standard deviation	10.77	4.42	43.25	16.00
Skewness	-0.94	-0.50	0.66	-0.29
Kurtosis	5.89	5.06	4.32	2.98

Figure 3.1 Prospective utility of momentum and market excess returns for different evaluation horizons and different transaction costs
The horizontal axis displays the evaluation horizon under which prospective utility (vertical axis) is calculated and the vertical axis measures the cumulative prospective utility of an investment strategy. The solid line represents market excess returns (ER), whereas the dashed lines represent momentum returns (MOM) for annual transaction costs from zero to ten percent. The sample period is 1963:07 to 2005:12.

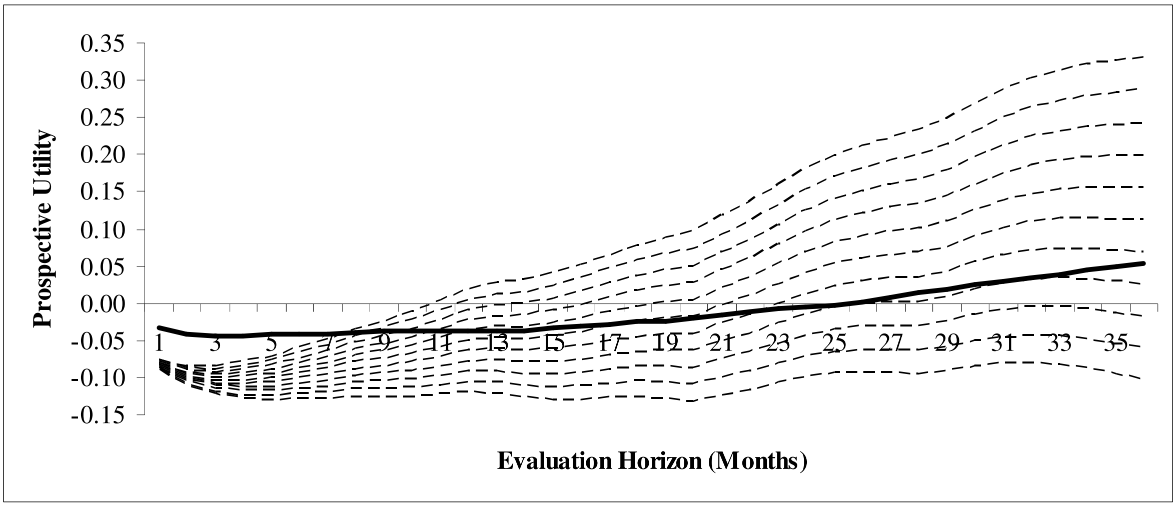
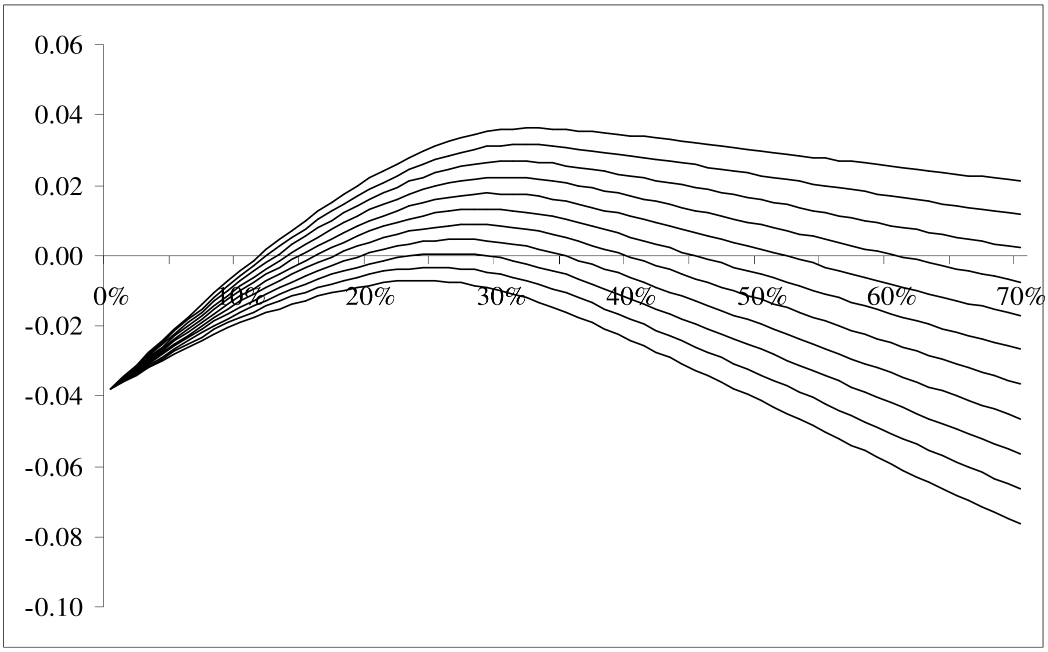
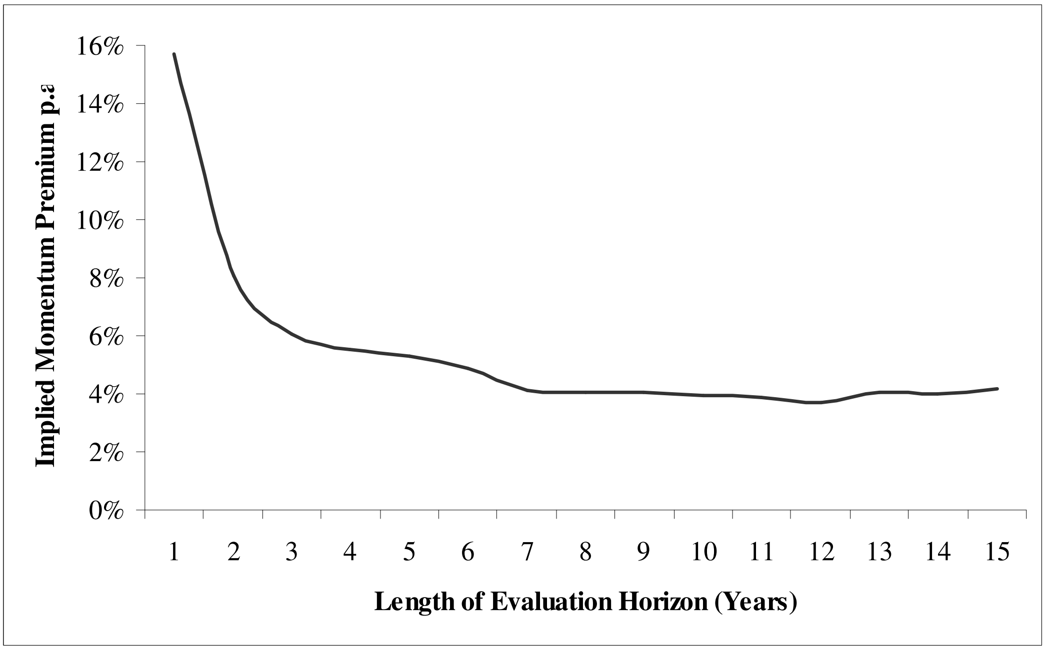


Figure 3.2 Optimal portfolio allocation and implied momentum premium
Panel (A) shows prospective utility (y-axis) for different portfolio shares (x-axis) of the momentum portfolio at a 12 months evaluation horizon. The lines correspond to transaction costs ranging from zero to ten percent p.a. The remaining portfolio share is allocated to the self-financing market portfolio. Panel (B) shows implied momentum premiums for evaluation horizons from one to fifteen years (no transaction costs imposed). The sample period is 1963:07 to 2005:12 for both panels.

Panel (A)



Panel (B)



Appendix to "A prospect-theoretical interpretation of momentum returns"

This appendix documents robustness of earlier findings by applying the identical method to two different, but popular momentum strategies. Appendix A shows results for the UMD momentum portfolio which is different from the earlier analysis in two important respects: first, the data period is much longer (including periods where momentum returns have been tentatively worse) and, second, winner and loser portfolios are formed by relying on the extreme 30 percent of stocks each, instead of ten percent. The formation period is 12 months. Data are taken from Kenneth French's web site and the sample is 1927:01 to 2004:12. Appendix B shows results for the strategy proposed by Jegadeesh and Titman (1993). Formation and holding period are 6 months both, and the strategy buys (sells) the top (bottom) decile of stocks. The sample period is 1961:01 to 1999:12 and data are from Chordia and Shivakumar (2002).

Appendix A. UMD momentum strategy

A1. Equation (3.1)

This equation shows results from regressing the monthly UMD momentum returns (MOM_t) on a constant and the three risk factor model of Fama and French (1996) using GMM and Newey-West standard errors. T-statistics are in parenthesis.

$$\underset{}{MOM_t} = \underset{[7.62]}{1.12} \ \underset{[-2.77]}{-\ 0.21\, ER_t} \ \underset{[-2.11]}{-\ 0.16\, SMB_t} \ \underset{[-3.08]}{-\ 0.43\, HML_t}\ ,\ R^2 = 22.5\%$$

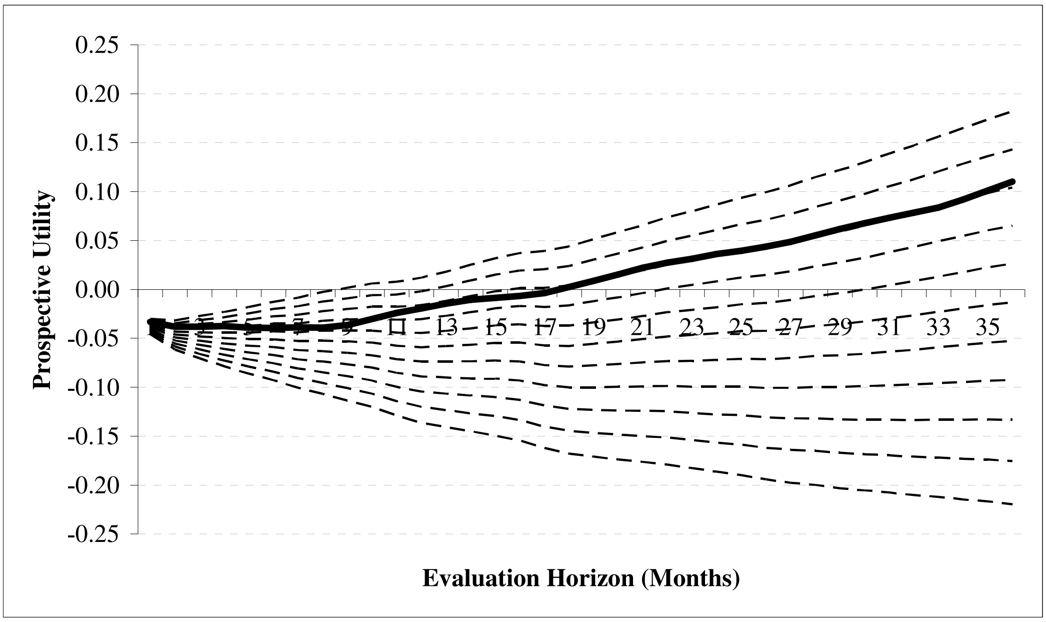
A2. Descriptive statistics of momentum and market excess returns

MOM and ER denote UMD momentum returns and the market excess return over the risk free rate, respectively. 12-month returns are obtained by chaining monthly returns. The sample period is 1927:01 to 2004:12.

	Monthly returns (in %)		12-months returns (in %)	
	MOM	ER	MOM	ER
Mean	0.75	0.65	9.09	8.19
Median	0.94	0.98	9.97	8.63
Maximum gain	18.38	38.18	76.70	154.73
Maximum loss	-50.92	-29.03	-75.80	-66.43
Standard deviation	4.73	5.49	15.27	21.61
Skewness	-3.00	0.21	-1.06	0.43
Kurtosis	30.86	10.63	9.11	6.53

A3. Prospective utility of momentum and market excess returns for different evaluation horizons and different transaction costs

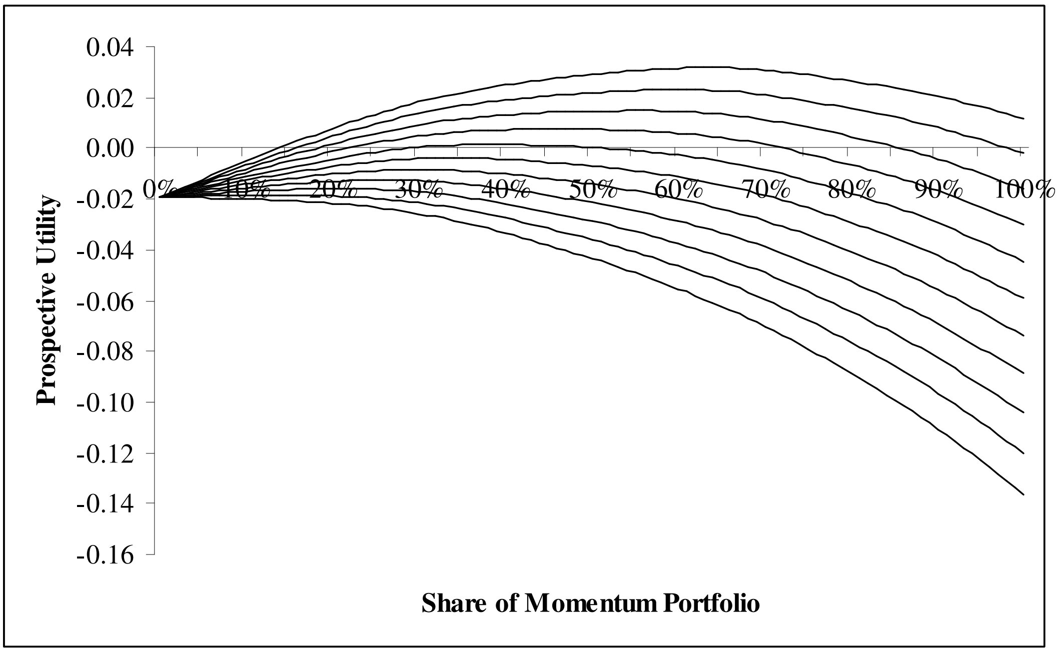
The horizontal axis displays the evaluation horizon under which prospective utility (vertical axis) is calculated and the vertical axis measures the prospective utility of an investment strategy. The solid line represents market excess returns (ER), whereas the dashed lines represent UMD momentum returns (MOM) for annual transaction costs from zero to ten percent. The sample period is 1927:01 to 2004:12.



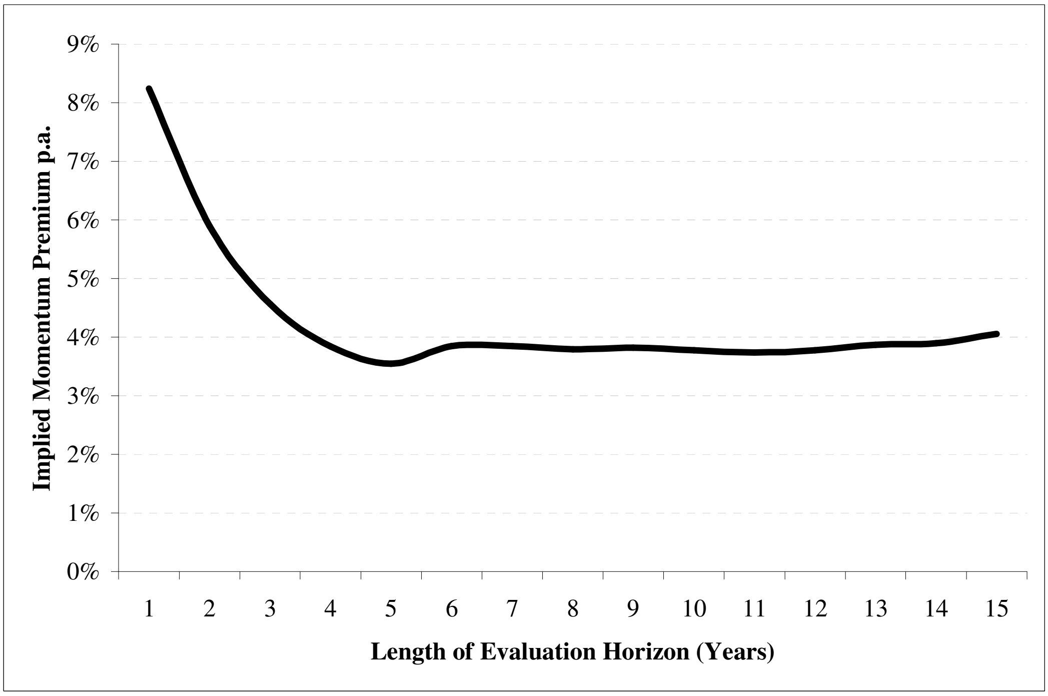
A4. Optimal portfolio allocation and implied momentum premium

Panel (A) shows prospective utility (y-axis) for different portfolio shares (x-axis) of the momentum portfolio at a 12 months evaluation horizon. The lines correspond to transaction costs ranging from zero to ten percent p.a. The remaining portfolio share is allocated to the self-financing market portfolio. Panel (B) shows implied momentum premiums for evaluation horizons from one to fifteen years (no transaction costs imposed).

Panel (A)



Panel (B)



Appendix B. Momentum strategy with a six months formation and holding period

B1. Equation (3.1)

This equation shows results from regressing the monthly momentum returns (MOM_t) on a constant and the three risk factor model of Fama and French (1996) using GMM and Newey-West standard errors. T-statistics are in parenthesis.

$$\underset{}{MOM_t} = \underset{[5.79]}{1.13} - \underset{[-1.20]}{0.11}\, ER_t - \underset{[-3.71]}{0.69}\, SMB_t - \underset{[-3.73]}{0.52}\, HML_t \quad , \; R^2 = 17.64\%$$

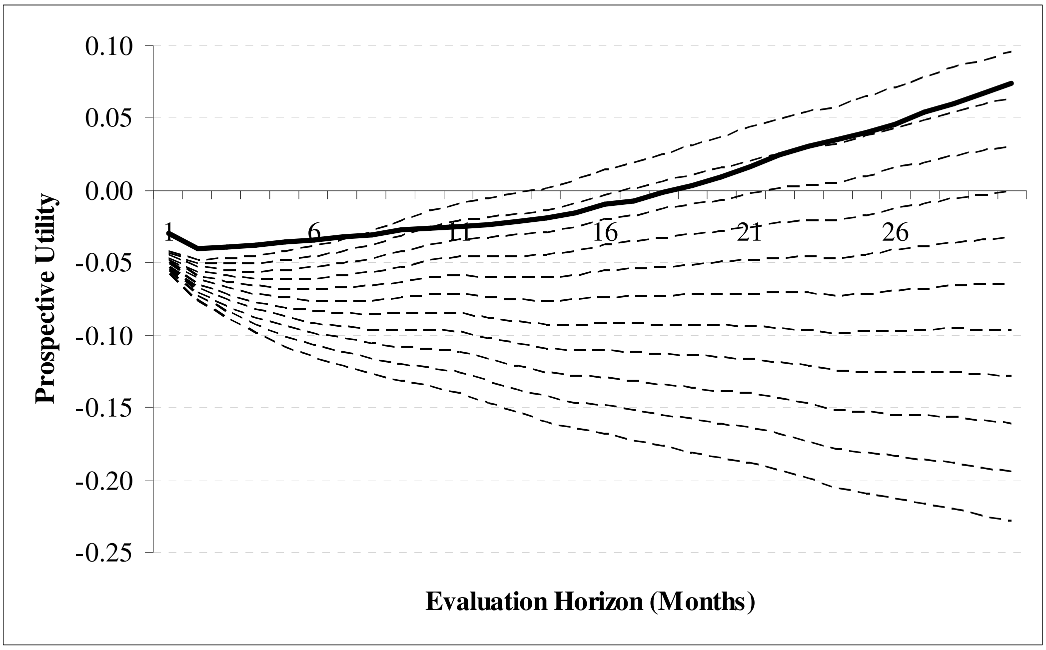
B2. Descriptive statistics of momentum and market excess returns

MOM and ER denote momentum returns and the market excess return over the risk free rate, respectively. 12-month returns are obtained by chaining monthly returns. The sample period is 1961:01 to 1999:12.

	Monthly returns (in %)		12-months returns (in %)	
	MOM	ER	MOM	ER
Mean	0.78	0.57	9.19	6.45
Median	1.39	0.83	10.96	8.49
Maximum gain	14.48	16.05	62.14	54.16
Maximum loss	-36.52	-23.13	-46.32	-45.76
Standard deviation	5.41	4.38	18.15	15.36
Skewness	-2.64	-0.51	-0.50	-0.33
Kurtosis	17.01	5.40	3.44	3.16

B3. Prospective utility of momentum and market excess returns for different evaluation horizons and different transaction costs

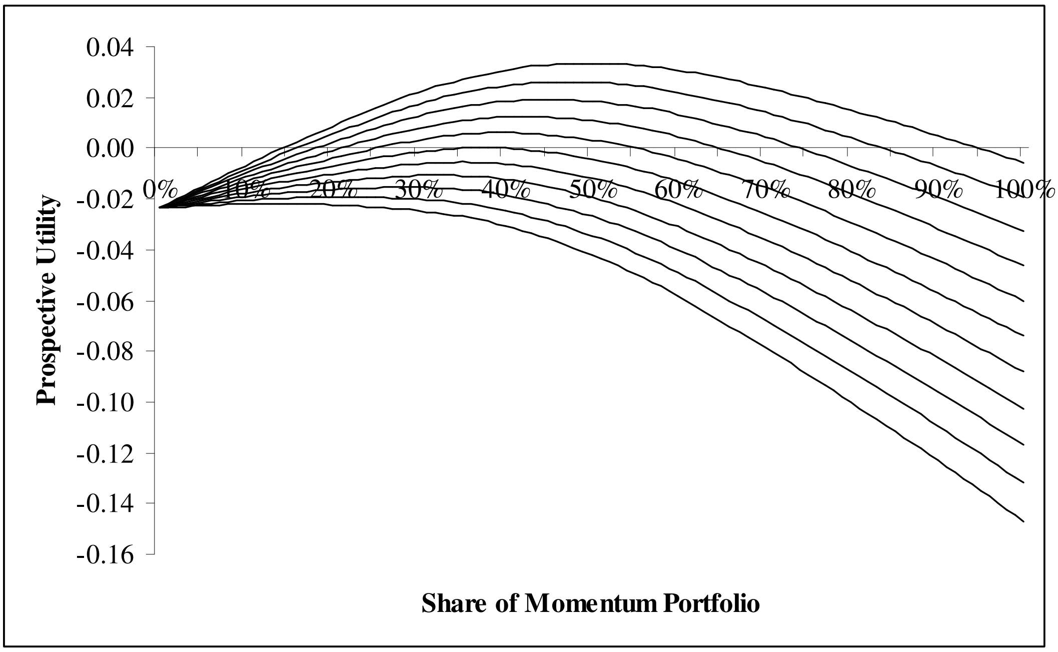
The horizontal axis displays the evaluation horizon under which prospective utility (vertical axis) is calculated and the vertical axis measures the prospective utility of an investment strategy. The solid line represents market excess returns (ER), whereas the dashed lines represent momentum returns (MOM) for annual transaction costs from zero to ten percent. The sample period is 1927:01 to 2004:12.



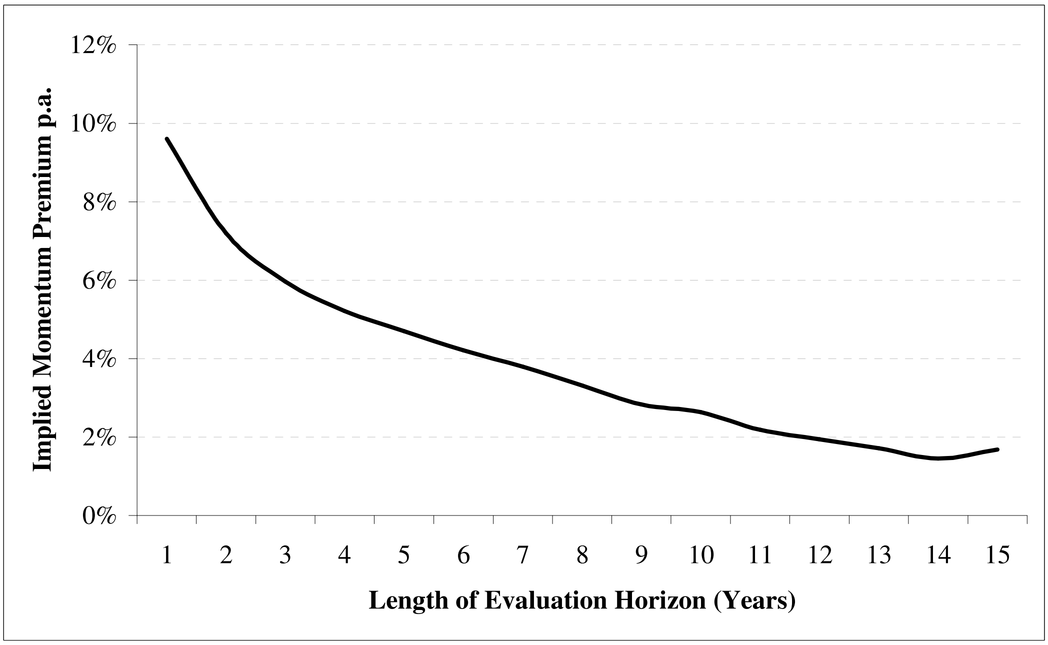
B4. Optimal portfolio allocation and implied momentum premium

Panel (A) shows prospective utility (y-axis) for different portfolio shares (x-axis) of the momentum portfolio at a 12 months evaluation horizon. The lines correspond to transaction costs ranging from zero to ten percent p.a. The remaining portfolio share is allocated to the self-financing market portfolio. Panel (B) shows implied momentum premiums for evaluation horizons from one to fifteen years (no transaction costs imposed).

Panel (A)



Panel (B)



Chapter 4: Myopic loss aversion and the cross-section of U.S. stock returns: Empirical evidence[*]

4.1 Introduction

This chapter shows that an application of prospect theory to asset pricing helps to explain the cross-section of U.S. stock returns. Of course, there are plenty of models which claim to explain cross-sectional returns. However, the recent study by Lewellen, Nagel and Shanken (2006) has convincingly demonstrated that these models lack generality. All of them perform well on the 25 Fama-French portfolios but almost none of them is very useful in explaining other kinds of cross-sections of U.S. stock returns that have been used in earlier empirical research. These cross-sections include the sorting of U.S. stocks according to their book to market ratio, to their prior returns or to their industry classification. Understanding generality of an asset pricing model in this sense, existing models seem to be somewhat specific.

As a contribution towards identifying an asset pricing approach with a higher degree of generality, we rely on Benartzi and Thaler (1995) who apply prospect theory to explain the U.S. equity premium puzzle. Prospect theory assumes that investors are loss averse, i.e. utility functions have a kink at an exogenous reference point. Reference points are set according to particular situations from the viewpoint of individuals. Furthermore, Benartzi and Thaler (1995) use the observation that individual and institutional investors often evaluate portfolios after one-year-periods to introduce myopic behavior.[31]

Combining these elements yields myopic loss averse investors who suffer more from losses than from gains of the same size and who pay attention to moments of short horizon returns and not to long horizon properties of return distributions. Under this modeling device, Benartzi and Thaler show that investors' utility from holding a

[*] This chapter is based on a paper with the same title co-authored with Lukas Menkhoff (Leibniz Universität Hannover).

[31] Myopia and loss aversion have become widely used tools to describe individual decision making (see Thaler, Tversky, Kahneman, and Schwartz, 1997, Waldfogel, 2005, or Langer and Weber, 2007, for applications and discussions).

diversified stock portfolio is not significantly different from earning the risk-free rate.[32] This result motivates to transfer this approach from pricing the market to pricing the cross-sections of returns and we find indeed that a universe of 115 different portfolios – covering the focus of interest of most empirical asset pricing papers – yields the same prospective utility as the broad market portfolio. This is a new finding as one approach is helpful in explaining not just one but all relevant cross-sections examined before.

Prospect theory (Kahneman and Tversky, 1979) and its main constituent, loss aversion, have long been a promising way to address asset pricing puzzles. As noted above, Benartzi and Thaler (1995) provide an early application. Barberis and Huang (2001) show how a high mean of stock returns, excess volatility and a value premium in the cross-section of stocks may occur in an economy with loss averse investors. Barberis, Huang and Santos (2001) demonstrate in calibration exercises how loss aversion over financial wealth fluctuations helps explain several aggregate market phenomena such as the equity premium puzzle, the risk-free rate puzzle and predictability in the time-series of stock returns. Most recently, Berkelaar, Kouwenberg and Post (2004) show that loss aversion significantly reduces the share of stock holdings in an optimal portfolio when investors have short planning horizons, Barberis, Huang, and Thaler (2006) apply the prospect-theoretical framework to make sense of the stock market participation puzzle (cf. Mankiw and Zeldes, 1991), and Menkhoff and Schmeling (2006) use prospect utility to explain high momentum returns (Jegadeesh and Titman, 2001).

This chapter addresses another important issue which is yet not well understood: is myopic loss aversion helpful in understanding the cross-sectional spread in U.S. stock returns? Motivated by recent advice of Lewellen, Nagel and Shanken (2006) we examine a comprehensive set of portfolios to test the power of this approach in explaining several market anomalies (e.g. value stocks, momentum stocks, contrarian strategies) and standard benchmark portfolios (e.g. the 25 Fama-French portfolios or 30 industry portfolios). We find that several cross-sectional stock return anomalies are well captured under the prospect-theoretical metric. Specifically, the ostensibly anomalous returns of e.g. momentum, value or contrarian portfolios do not outperform the market portfolio from a utility perspective when investors are characterized by myopic loss aversion.

[32] Empirical and experimental evidence suggests that both laymen and professional investors are subject to myopic loss aversion (see for example Haigh and List, 2005).

This finding indicates that the way investors assess the utility of portfolios may be important for asset pricing. In a next step, we thus interpret myopic loss aversion itself as a price relevant risk factor and include it into a conventional multi-factor asset pricing approach in the Fama-MacBeth (1973) regression tradition. We show that portfolios with unfavorable distributional properties for loss-averse investors demand a higher premium cross-sectionally. The inclusion of this prospect-theory based factor robustly generates insignificant alpha estimates of an economically sensible size and easily survives the inclusion of a variety of risk factors proposed in the literature.

The rest of the chapter proceeds as follows. Section 4.2 describes the data used in the empirical analysis, Section 4.3 details the methodology and results. We perform several robustness checks in Section 4.4 and conclude in Section 4.5.

4.2 Data

This empirical analysis fully relies on data of stock portfolios that has been used extensively in earlier research. Thus, our contribution with respect to data is that we use –inspired by Lewellen, Nagel and Shanken (2006) – a broader set of portfolios compared to earlier studies in this line of literature which mostly analyze the 25 Fama-French portfolios.

Specifically, we include the following portfolios in our empirical analysis:[33]

(a) 10 portfolios formed on book-to-market (BE/ME)
(b) 10 portfolios sorted on the dividend-price ratio (D/P)
(c) 10 portfolios sorted on size (ME)
(d) 25 Fama-French portfolios (FF)
(e) 10 portfolios sorted on short-term performance, i.e. the return over the prior month (Prior 1-0)
(f) 10 portfolios sorted on momentum, i.e. the return over the prior 12 months (Prior 12-2)
(g) 10 portfolio sorted in long-term performance, i.e. the return over the prior five years (Prior 60-13)
(h) 30 industry portfolios (30 Industries),

which gives a total of 8 portfolio cross sections and 115 portfolios under consideration which will be examined jointly and separately. Returns are monthly and the sample

[33] All portfolio return data is obtained from Prof. Kenneth French's web site.

period is January 1936 to December 2005. We deflate all returns with monthly CPI data obtained from Prof. Robert Shiller's web page. Returns on the market portfolio, the HML and SMB factors used in this study are again collected from Prof. French's web site.

We will provide only short descriptions of these portfolios because they are subject to a large amount of previous research and are described in detail on the website of Prof. French. First of all, the portfolios sorted on BE/ME and D/P are a means to look at the return spread of glamour (low BE/ME, D/P) versus value stocks (high BE/ME, D/P) (cf. Fama and French, 1998). The portfolios sorted on size (ME) have been constructed to investigate the so-called size premium (cf. Fama and French, 1992). The 25 Fama-French portfolios (FF) have become the benchmark each asset-pricing model has to surmount (Fama and French, 1993). The following three sets of portfolios are formed on past prices. The Prior 1-0 portfolios are formed on short-term performance. Jegadeesh (1990) found that past short-term losers (over the last month) earn higher returns than past winners subsequently. The ten momentum portfolios (Prior 12-2) were analyzed in Jegadeesh and Titman (1993, 2001). Portfolios are formed on prior 12 months performance. Past winners continue to outperform past losers. The long-term reversal portfolios (Prior 60-13) originate from the study of DeBondt and Thaler (1985) who show that past long-term losers outperform past long-term winners by a substantial amount. Finally, the 30 industry portfolios are common in empirically testing asset-pricing models (cf. Lewellen, Nagel and Shanken, 2006) since they are based on a somewhat more natural sorting procedure that does not include past security prices. So we also include these industry portfolios here.

Descriptive statistics are given in **Table 4.1** and reveal the usual pattern observed in the spread of returns for these portfolios. For example, value stocks (high BE/ME) earn higher returns than growth stocks (low BE/ME), small stocks (Low ME) command a larger return than large stocks (high ME), and past winners (high prior 12-2 return) outperform past losers (low prior 12-2) by a significant amount. Large differences of up to 0.65% p.m. can be observed even among the industry portfolios.

However, apart from the first moments, there is also considerable spread in higher order moments. For example, small stocks (low ME) have a much higher kurtosis than large stocks (high ME) which is quite unattractive to a loss averse investor and might (partially) compensate for the higher returns of small stocks. The same is true for portfolios sorted on BE/ME. Value stocks have a kurtosis that is higher by a factor of about three compared to growth stocks which might make the higher returns of value stocks less attractive. For the prior 12-2 (momentum) portfolios we observe that past winners not only have higher returns than past losers but also a much lower skewness, a feature clearly being unattractive to loss averse investors.

That said, the ultimate goal of the next sections is to cast this informal discussion of cross-sectional moments into a fully developed utility framework. This serves to analyze whether stock returns are in equilibrium when looking at them from the perspective of myopically loss averse investors.

4.3 Empirical approach and results

4.3.1 Methodology

We closely follow the methodology employed by Benartzi and Thaler (1995) in their seminal paper to ensure comparability of results. Their intuition is to apply the prospect theory to investment decisions because prospect theory is a positive theory of decision making with a very robust empirical foundation. So, we assume that investors assess stock portfolios relative to the total stock market by effectively showing short-term evaluation horizons of one year, loss aversion and miscalibrated probability judgments (cf. recently Barberis, Huang and Thaler, 2006).

Therefore, we employ cumulative prospective utility in the sense of Kahneman and Tversky (1979) and Tversky and Kahneman (1992) which has a value function $v(\cdot)$

$$v(\chi) = \begin{cases} \chi^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-\chi)^{\beta} & \text{if } x < 0 \end{cases} \tag{4.1}$$

where χ denotes a payoff, α and β are curvature parameters and λ is the coefficient of loss aversion. Tversky and Kahneman (1992) estimate α and β to be 0.88 yielding risk averse (risk seeking) behavior in the domain of gains (losses). They also estimate λ to be 2.25 which leads to the result that a loss causes a (more than) twofold reduction in the value of a return compared to the value increase for a gain of the same absolute size.

Furthermore, under cumulative prospect utility investors also have miscalibrated probability judgments in the sense of an overweighting of very unlikely outcomes and on underweighting of highly probable outcomes. Tversky and Kahneman (1992) employ the following parameterization for the perceived probability π_i and outcome *i* which is adopted by Benartzi and Thaler (1995):

$$\pi_i = w\left(P_i\right) - w\left(P_i^*\right) \qquad (4.2)$$

where π_i is the weighted probability of obtaining outcome *i*, P_i is the actual probability of outcome *i* and P_i^* is the probability of realizing an outcome as least as good as *i*. The weighting of probabilities is obtained via the following weighting function:

$$w(p) = \frac{p^\gamma}{\left(p^\gamma + \left(1 - p^\gamma\right)\right)^{\frac{1}{\gamma}}}. \qquad (4.3)$$

From (4.2) it can be seen that the perceived probability of event *i* does not only depend on that event's probability but also on the probabilities of the other outcomes. The parameter γ in (4.3) is estimated to be 0.61 (0.69) for the domain of gains (losses). Assembling the pieces in (4.1)-(4.3), the cumulative prospect utility (henceforth CPT) of a gamble G, V(G), is computed in the standard way by summing over the probability weighted values, i.e.

$$V(G) = \sum_i \pi_i v\left(\chi_i\right). \qquad (4.4)$$

In order to empirically calculate the CPT of a given portfolio it is necessary to calculate π_i which in turn depends on the "true" probabilities P_i. Benartzi and Thaler (1995) obtain the P_i's by bootstrapping and discretizing the return distribution which is also the method we employ here. For a given evaluation horizon *n*, e.g. *n* = 12 months for an annual horizon, one draws with replacement 1,000,000 *n*-months returns from the return history and ranks them in descending order. One hundred intervals of 10,000 *n*-months returns (beginning with the highest returns) are formed and then the mean return for each interval is computed. This yields one hundred pairs of (χ_i, P_i) where P_i=1/100 for all *i*. With these pairs in hand it is straightforward to compute the CPT in (4.4) for a desired return series and sample period.

4.3.2 Portfolio performance under cumulative prospect utility

The prospect utility of all 115 portfolios under consideration is not significantly different from the market portfolio's utility, although many of these portfolios have significant excess returns compared to the aggregate market which cannot be easily explained by standard asset pricing models (cf. Cochrane, 2006).

In order to provide an easily accessible graphical presentation of the portfolio performances under consideration here, we compute CPT's for all portfolios over rolling 60 months periods with a 12 months skipping. That means we compute the first CPT for portfolio *k* over the period January 1936 to December 1940, the second CPT for portfolio *k* over the period January 1937 to December 1941 and so on. This yields a total of 66 CPT's for each of the 115 portfolios. Following Benartzi and Thaler (1995) we compare the CPT of a portfolio to a benchmark. Whereas they use the bond return as a natural benchmark for comparison with the aggregate stock market return, we rely on the latter as the benchmark for our portfolio returns. We do this, since for a typical investor the aggregate market seems to be the natural benchmark when evaluating the performance of a specific stock portfolio.[34] Therefore, we also compute the CPT of the aggregate U.S. stock market return over the 66 five year samples and report the difference between a portfolio's CPT and the market's CPT in Figure 4.1. Shown are the median as well as 10 and 90 percent point of these CPT's for each portfolio *k*. All calculations are CPI deflated.

As can be seen from Figure 4.1, all portfolios have median (and mean, though not shown) CPT's near zero. Although some (median) utilities are higher or lower than the utility from holding the market portfolio, the distribution of CPT's around the median – as shown by the 90% confidence interval presented in these graphs – does not indicate that the utility from any portfolio is significantly different from that of the aggregate market: all portfolios fail to systematically yield positive utility compared to the aggregate real market returns over the last 70 years.

We conclude that, assuming myopic loss aversion correctly describes the utility which investors receive from holding certain portfolios, the returns of various kinds of portfolios seem to be consistent with the notion of market equilibrium in such a kind of economy.

4.3.3 Cross-sectional analysis for all portfolios: Fama-MacBeth regressions

This section examines a core implication of the above analysis by showing that the risk of a portfolio as perceived by myopic and loss averse investors via prospective utility is a priced factor in the cross-section of returns. We find that prospective utility

[34] Descriptive statistics for the market (excess) return can be found in **Appendix 1**.

robustly explains cross-sectional returns in the presence of other pricing factors and that its relative contribution is remarkable.

In this section we run cross-sectional regressions of portfolio returns on risk factors (such as HML or SMB), portfolio characteristics (such as firm size) and on a pricing measure based on cumulative prospect theory. This CPT-based factor measures how much return a loss averse investor demands for holding a certain stock or portfolio with given risk characteristics. The construction of this measure proceeds as follows. We calculate the prospective utility given (as shown in (4.4)) for the real market return (call it V^M). Then, for a given portfolio *k* we first demean the time series of returns to obtain a mean zero return series $\tilde{r}_t^k$ and numerically solve for the return θ^k that makes the prospective utility of the return series equal to the prospective utility of the market portfolio. Thus we numerically solve for the θ^k that makes the left- and right-hand side of the following equation hold as close as possible

$$V\left(\tilde{r}_t^k + \theta^k\right) = V^M . \tag{4.5}$$

Since we are still employing (monthly overlapping) annual returns, θ^k directly gives the annual return that a myopic loss averse investor demands for holding portfolio *k* with all its other moments, e.g. variance, skewness, kurtosis, being unchanged. Therefore, portfolios with second or higher order return moments that are unfavorable for a loss averse investor – most importantly a large variance, negative skewness or high kurtosis – should demand a higher return θ^k and vice versa. We therefore expect to see cross-sectionally that at a given point in time, *t*, θ_t^k is a priced factor.

Moreover, this required return (derived from prospective utility) has an intuitive meaning. A one percent increase in this factor should lead to a one percent increase in returns. Therefore, when cumulative prospect utility as calibrated by Tversky and Kahneman (1992) is the correct utility function for investors, we should find a one to one relation between our estimate of the factor θ^k and returns r^k.

For the Fama-MacBeth regressions we calculate the required return θ^k for periods of 60 months that have an overlapping structure of twelve months. This means for example, that we estimate the required return for January 1936 to December 1940 to obtain an estimate of θ^k for January 1940 to December 1940 and then shift the estimation window to January 1937 to December 1941 which yields the estimated return for January 1941 to December 1941 and so forth. Therefore, our sample effectively starts in January 1940. In the cross-sectional regressions we regress returns on the estimated risk factor θ^k and other factors from the earlier literature, e.g. HML, SMB or firm size.[35]

Results from the regressions for all 115 portfolios jointly are shown in **Table 4.2**. The first specification (1) just includes the estimated required return as defined above ($\hat{\theta}$) and shows that the coefficient on $\hat{\theta}$ is significantly positive, albeit smaller than one.

It is noteworthy, however, that this factor is powerful for pricing the large cross-section of portfolios and that the estimated intercept is not significantly different from zero. Furthermore, following Lewellen, Nagel and Shanken (2006) we take serious the size of the estimated intercept. The value of 0.11% p.m. (see column (1) in Table 4.2) corresponds to a real risk-free rate of roughly 1.3% p.a. which seems to be a much more reasonable number than the implied risk-free rates from traditional asset pricing models (cf. Lewellen, Nagel and Shanken, 2006).

The next columns (2) to (7) include further cross-sectional pricing factors in the Fama-MacBeth regressions as they were employed in earlier papers. Specifically, the second specification picks up the core ingredient of consumption based asset pricing models and thus adds log real consumption growth (cf. Cochrane, 2004). Interestingly, it does not enter significantly and does not change the general conclusion for the intercept and slope obtained from specification (1). Column (3) adds HML and SMB as the most prominent pricing factors in the literature. Again, the alpha from this regression is small and the coefficient on $\hat{\theta}$ is highly significant although HML enters significantly. For comparison, we also show results for the Fama-French (1996) three factor model in column (4). For this large cross-section of returns the estimated alpha is highly significant and much too large to represent a reasonable risk free rate ($0.62 \times 12 \approx 7.4\%$) whereas the estimated risk premium on the beta factor is not significant and much too small, implying an annual equity risk premium of only $0.09 \times 12 \approx 1.1\%$. However, we know that this risk premium is above 6% p.a. from the early paper of Mehra and Prescott (1985) and the real annual market excess return is indeed about 7 % in our sample.

Column (5) adds firm size which enters significantly negative as can be expected from earlier studies which show that the characteristic itself is priced although the

[35] Descriptive statistics for the three Fama-French risk factors can be found in Appendix 1.

corresponding risk factor (here SMB) is included in the cross-sectional regression (Daniel and Titman, 1997).

Finally, we add other measures of non-linear risk in column (6), namely downside and upside betas as well as coskewness and cokurtosis. This serves to investigate whether the use of our CPT risk premium θ^k is dominated by these variables that also proxy for non-linear risk. Downside betas (β^-) and upside betas (β^+) are computed as in Ang, Chen and Xing (2006):

$$\beta^- = \frac{\operatorname{cov}\left(r^k, r^m \mid r^m < \mu^m\right)}{\operatorname{var}\left(r^m \mid r^m < \mu^m\right)} \tag{4.6}$$

$$\beta^+ = \frac{\operatorname{cov}\left(r^k, r^m \mid r^m > \mu^m\right)}{\operatorname{var}\left(r^m \mid r^m > \mu^m\right)} \tag{4.7}$$

where μ^m denotes the mean return. Intuitively, upside and downside betas measure how much covariation an asset has with the market in good and bad times. Therefore, portfolios with higher upside betas (downside betas) should command lower (higher) mean returns.

Coskewness (coskew) and cokurtosis (cokurt) are computed as follows (see Ang, Chen and Xing, 2006):

$$\text{coskew} = \frac{E\left[\left(r^k - \mu^k\right)\left(r^m - \mu^m\right)^2\right]}{\sqrt{\operatorname{var}\left(r^k\right)} \operatorname{var}\left(r^m\right)} \tag{4.8}$$

$$\text{cokurt} = \frac{E\left[\left(r^k - \mu^k\right)\left(r^m - \mu^m\right)^3\right]}{\sqrt{\operatorname{var}\left(r^k\right)} \operatorname{var}\left(r^m\right)^{3/2}} \tag{4.9}$$

Harvey and Siddique (2000) predict that lower coskewness should be associated with higher expected returns since portfolios that have low returns when the market realizes more extreme returns are riskier. Similarly, assets with higher cokurtosis (cf. Dittmar, 2002) should show higher returns in order to compensate for the risk of obtaining unfavorable returns when market returns are negatively skewed.

As can be seen from column 6 in Table 4.2, the down- and upside risk measures as well as the higher-order co-moments are not helpful in pricing this large cross-section of returns. This is different from the significant findings of Ang, Chen and Xing (2006) but may be explained by the fact that we use portfolio returns and not individual stocks as in their study. Portfolio returns are different from individual stock returns, since portfolio characteristics are much more stable than characteristics of individual firms (cf. Cochrane, 2004).

The last column in Table 4.2 shows results when we include the CPT-based factor and all other factors considered above jointly in the regressions. The CPT factor seems to dominate all other variables which is evident from the large t-statistic of more than six and which dwarfes the significance of all other variables. Therefore, it seems unlikely that risk, as perceived by myopically loss averse investors, is well proxied for by linear and non-linear pricing factors employed in earlier work.

4.3.4 Cross-sectional analysis for the different groups of portfolios

Given the results in Table 4.2 it is natural to ask whether this approach is also helpful for pricing smaller cross-sections of portfolio returns. Therefore, we run Fama-MacBeth regressions for each of the eight groups of portfolios separately, e.g. for the ten BE/ME portfolios etc.

Results are shown in **Table 4.3**. For each group of portfolios we give results for the model where the market beta is replaced by the estimate of θ^k.(the CPT based model) and for the Fama-Fench three factor model. As is evident from the table, results for the coefficent θ^k are remarkably stable when employing each of these smaller cross-sections. Moreover, estimated intercepts are insignificant and of economically sensible size for the CPT based model, which is not true for the pure Fama-French three factor model.

This finding is especially comforting, since prospect theory is a general framework of decision making under risk which should give valid results no matter which particular set of portfolios one concentrates on.

4.4 Robustness tests

4.4.1 Randomization of test assets and test periods

As a first robustness check we randomize over the test assets used in the Fama-MacBeth regressions, i.e. we run 5,000 Fama-MacBeth regressions with the premium

θ^k, HML and SMB as explanatory variables where in each run only 60 portfolios are randomly selected (without replacement) as test assets.

The first column of **Table 4.4**, Panel A, reports the mean of the 5,000 estimated coefficient vectors along with empirical 95% confidence intervals in curly brackets. As is evident from this exercise, the results shown in Table 4.2 are not sensitive to the specific choice of test assets used. The estimated α is still around 0.2 per month and insignificant while the CPT risk premium factor θ^k still is significantly priced with a mean coefficient of around 0.6 and tight confidence intervals.

Secondly, we investigate whether the specific test periods used are critical to our results. Therefore, we run 5,000 repetitions of the Fama-MacBeth procedure with the same risk factors as above, where in each repetition we randomly select 396 out of the available 792 months as the test period (again, drawing is without replacement). The months selected need not be consecutive. Mean coefficient vectors and empirical confidence intervals can be found in the second column of Table 4.4, Panel A. The results are highly similar to the results obtained above so we conclude that the specific choice of test period does not seem to drive our results.

Finally, column three of the same table and panel shows results when we jointly randomize over test assets and test periods as described above. Again, the results remain unchanged.

4.4.2 Randomization of explanatory variables

As an alternative robustness check we test whether our results are spurious in the sense that the estimate of θ^k used in the Fama-MacBeth regressions has unfavorable statistical properties of some (unknown) form that accidentally generates the results documented above.

Therefore, we proceed as follows. We randomly match each asset return series with the estimated factor risk premia (θ^k, HML, SMB) of another series (drawing with replacement), apply the Fama-MacBeth procedure, save the estimated coefficients and repeat this procedure 5,000 times. This procedure allows us to test, whether our coefficient estimates obtained from the original cross-sectional regressions are spurious.

Table 4.4, Panel B gives the original coefficient estimates in the second column and the mean coefficient estimates from the bootstrap procedure in the third column. These show that our estimated slope coefficients are uniformly zero on average, i.e.

unbiased. The fourth and fifth column of the same Panel B shows the standard deviation of estimated slope coefficients and bootstrap t-test statistics, respectively. It can be seen, that the coefficient on the CPT risk premium is significantly different from zero and that HML also adds some statistically significant explanatory power.

4.5 Conclusions

Prospect theory is an established and empirically robust positive theory of decisions under risk (Kahneman and Tversky, 1979). We follow the method introduced by Benartzi and Thaler (1995) to apply prospect theory in order to investigate the cross-section of U.S. stock returns. We find that myopic loss aversion helps to explain the returns of a large universe of portfolios to a degree that could make it an interesting ingredient for asset pricing models in general.

Indeed, under the prospect-theoretical metric, portfolios' return distributions deliver near zero utility when compared to the market portfolio and the perceived riskiness of return distributions under myopic loss aversion is a systematically priced factor in the cross-section of returns that tends to dominate other popular measures of risk. Furthermore, the inclusion of this perceived risk for a myopic loss averse investor yields empirically plausible estimates of the real risk-free rate, a point recently reinforced by Lewellen, Nagel and Shanken (2006).

The approach chosen here is not derived from a formal theoretical model but relies on an empirically well established positive theory of decision making under risk. Some earlier successful applications – in particular Benartzi and Thaler (1995) – suggest that myopic loss aversion may be helpful in explaining another big open question, namely the cross-sectional pricing of U.S. stock returns. Findings are quite supportive to this approach and may stimulate further research to better integrate myopic loss aversion into a more general understanding of asset prices.

Table 4.1 Descriptive statistics

This table shows the mean, standard deviation (std), skewness (skew) and kurtosis (kurt) for monthly portfolio returns used in the empirical analysis. The sample is January 1936 to December 2005

	mean	std	skew	kurt		mean	std	skew	kurt
BE/ME					FF25				
Low	0.87	5.03	-0.24	5.20	Small - Low	0.72	9.14	0.36	7.14
2	0.96	4.83	-0.42	6.31	2	1.16	7.76	0.37	9.01
3	0.96	4.73	-0.47	6.67	3	1.33	7.18	0.87	15.15
4	0.96	4.74	-0.35	7.04	4	1.49	6.48	0.28	10.77
5	1.10	4.40	-0.47	6.45	Small - High	1.67	7.52	1.77	27.12
6	1.14	4.62	-0.54	6.51	2 - Low	0.94	7.39	0.18	8.00
7	1.14	4.93	0.07	8.09	2	1.20	6.29	-0.07	8.32
8	1.29	4.98	-0.21	7.32	3	1.32	5.69	-0.21	7.83
9	1.32	5.80	0.41	12.86	4	1.40	5.81	-0.21	8.08
High	1.41	7.23	0.70	17.85	2 - High	1.56	6.84	0.21	10.53
D/P					3 - Low	0.95	6.49	-0.24	5.78
Low	0.98	5.70	-0.36	5.60	2	1.20	5.62	-0.47	7.00
2	0.97	5.06	-0.35	5.89	3	1.24	5.37	-0.39	7.92
3	0.97	4.86	-0.27	6.94	4	1.34	5.22	-0.25	6.53
4	1.03	4.52	-0.39	5.22	3 - High	1.48	6.48	0.07	9.24
5	0.95	4.45	-0.36	6.13	4 - Low	0.99	5.68	-0.29	5.34
6	1.01	4.45	-0.35	5.58	2	1.01	5.22	-0.50	7.22
7	1.08	4.45	-0.43	5.30	3	1.25	5.09	-0.58	6.72
8	1.18	4.55	-0.28	6.89	4	1.27	5.32	-0.16	7.21
9	1.16	4.43	-0.25	5.70	4 - High	1.43	6.59	0.22	9.98
High	1.07	4.71	0.23	9.59	Big - Low	0.90	4.75	-0.27	5.73
ME					2	0.93	4.55	-0.32	6.47
Low	1.42	8.10	2.05	26.39	3	1.06	4.32	-0.37	6.10
2	1.28	7.07	0.57	12.95	4	1.11	4.88	0.05	7.80
3	1.26	6.34	-0.22	6.94	Big - High	1.17	6.18	0.49	13.95
4	1.24	6.11	-0.12	7.80					
5	1.22	5.84	-0.36	7.15					
6	1.16	5.51	-0.39	6.67					
7	1.17	5.43	-0.39	7.34					
8	1.09	5.11	-0.46	5.87					
9	1.05	4.78	-0.37	6.33					
High	0.91	4.32	-0.40	6.20					

Table 4.1 *(continued)*

	mean	std	skew	kurt		mean	std	skew	kurt
Prior 1-0					30 Industries				
Low	1.40	7.03	0.29	8.06	Autos	1.01	6.33	-0.08	5.66
2	1.39	5.93	0.66	10.14	Beer	1.16	5.77	0.12	6.82
3	1.32	5.20	0.27	8.68	Books	1.02	6.01	-0.23	6.31
4	1.09	4.98	0.05	7.88	BusEq	1.11	6.37	-0.29	5.19
5	1.05	4.83	0.27	10.49	Carry	1.17	6.78	0.17	7.54
6	1.03	4.62	-0.21	7.26	Chems	0.94	5.23	0.01	6.03
7	0.90	4.55	-0.39	7.11	Clths	1.11	6.31	-0.09	6.05
8	0.91	4.59	-0.65	5.75	Cnstr	1.02	5.93	-0.12	7.51
9	0.67	4.81	-0.77	6.59	Coal	1.45	8.67	1.32	12.12
High	0.53	5.72	-0.31	7.15	ElcEq	1.16	6.19	-0.15	5.25
Prior 12-2					FabPr	1.01	5.96	-0.13	6.82
Low	0.32	7.48	0.56	9.26	Fin	1.10	5.22	-0.33	5.92
2	0.74	6.16	0.46	11.82	Food	1.02	4.28	-0.19	6.08
3	0.84	5.37	0.47	11.92	Games	1.17	7.05	-0.27	5.59
4	0.91	4.99	0.24	11.02	Hlth	1.12	5.01	0.00	5.14
5	0.88	4.79	0.20	12.82	Hshld	1.00	4.76	-0.37	5.12
6	0.98	4.84	-0.19	9.83	Meals	1.24	6.49	-0.26	5.00
7	1.06	4.72	-0.28	7.96	Mines	0.93	6.38	-0.04	5.39
8	1.18	4.73	-0.33	6.45	Oil	1.15	5.37	0.02	5.46
9	1.26	5.08	-0.68	6.08	Other	0.80	5.80	-0.36	6.28
High	1.62	6.15	-0.55	5.18	Paper	1.02	5.16	-0.19	5.78
Prior 60-13					Rtail	1.07	5.33	-0.24	5.66
Low	1.33	6.88	0.59	7.89	Servs	1.17	7.04	-0.11	5.76
2	1.17	5.36	-0.05	8.21	Smoke	1.15	5.71	-0.05	5.92
3	1.18	4.96	-0.27	7.86	Steel	0.95	7.03	0.23	7.33
4	1.02	4.49	-0.47	6.63	Telcm	0.83	4.21	-0.13	5.20
5	1.05	4.51	-0.53	7.01	Trans	1.00	6.11	0.00	7.39
6	1.01	4.41	-0.65	6.79	Txtls	1.03	6.47	-0.26	6.53
7	1.05	4.67	-0.28	7.24	Util	0.89	4.46	0.01	5.60
8	1.00	4.87	-0.21	8.12	Whlsl	1.06	5.93	-0.36	6.33
9	0.97	5.19	-0.23	7.86					
High	0.93	6.00	-0.39	5.84					

Figure 4.1 Prospective utilities of all 115 portfolios in excess of the aggregate market

Simulated cumulative prospective utilities for the 115 portfolios under consideration minus the cumulative prospective utility of the market return. The middle line shows the median, the upper and lower line shows the simulated 90% confidence interval.

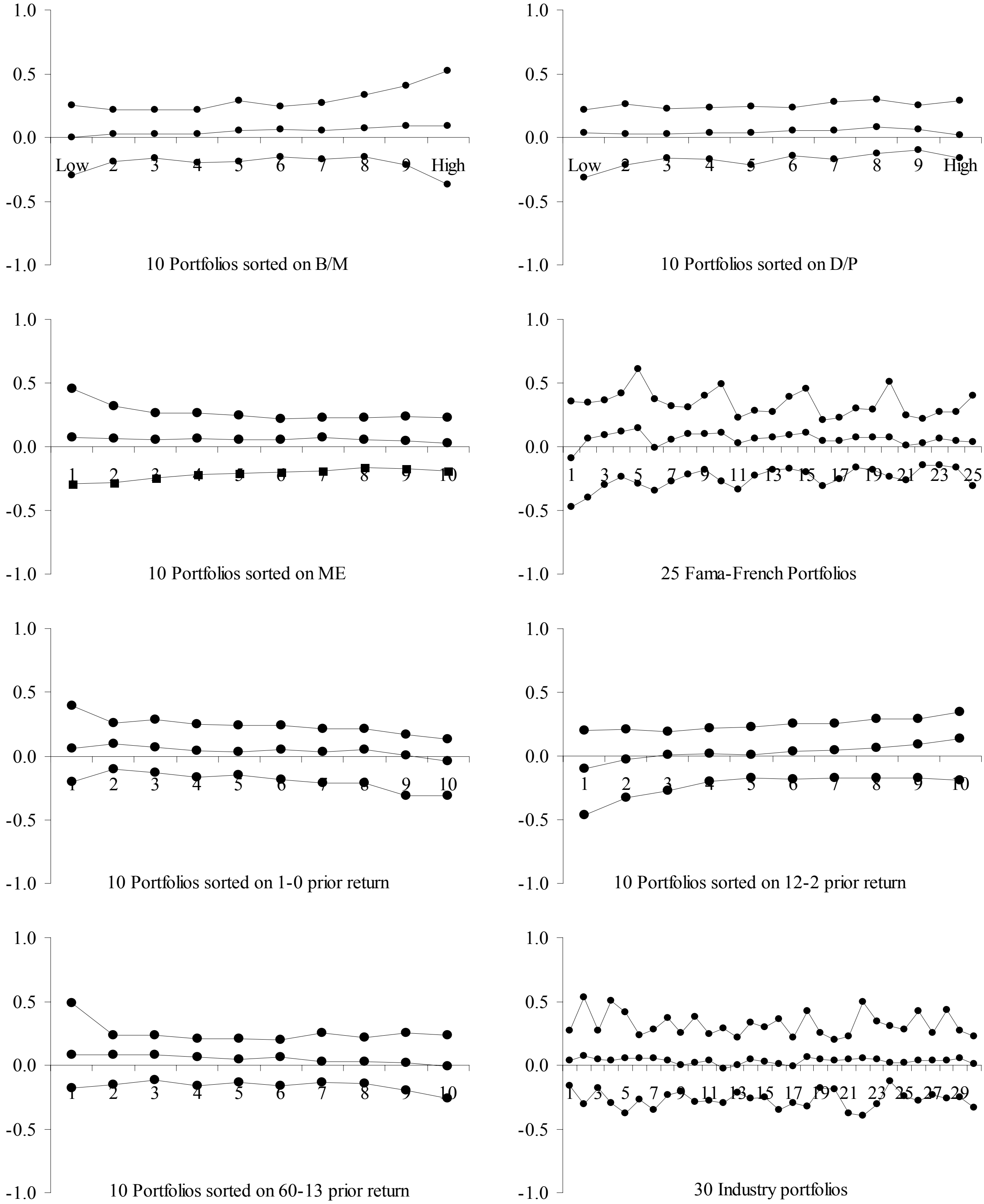


Table 4.2 Fama-MacBeth regressions for all portfolios
Results from Fama-MacBeth two-step regressions for the whole sample period January 1940 to December 2005 and for all 115 portfolios. T-statistics are in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Const.	0.11	0.13	0.19	0.62	0.21	0.83	0.14
	[0.59]	[0.58]	[1.14]	[4.39]	[1.24]	[5.05]	[0.68]
$\hat{\theta}$	0.61	0.41	0.66		0.66		0.86
	[3.61]	[2.31]	[5.09]		[5.14]		[6.30]
log Δc		0.03					
		[0.39]					
Beta				0.09			
				[0.46]			
HML			0.22	0.26	0.22	0.19	0.18
			[2.01]	[2.24]	[1.98]	[1.65]	[1.58]
SMB			0.01	0.14	-0.01	0.12	-0.00
			[0.06]	[1.18]	[-0.13]	[1.10]	[-0.05]
firm size					-0.29		-0.26
					[-2.57]		[-2.99]
Downside beta						0.06	-0.36
						[0.26]	[-1.87]
Upside beta						-0.08	-0.22
						[-0.40]	[-1.24]
Coskewness						0.17	0.11
						[0.24]	[0.17]
Cokurtosis						0.02	0.18
						[0.12]	[1.34]
R^2	0.08	0.15	0.29	0.32	0.29	0.37	0.41

Table 4.3 Fama-MacBeth regressions for different portfolio groups
Results from Fama-MacBeth two-step regressions for the whole sample period January 1940 to December 2005 and for different subsets from the universe of all portfolios. T-statistics are in brackets.

	Const.	$\hat{\theta}$	Beta	HML	SMB	R^2
10 BE/ME	0.18 [0.84]	0.62 [2.83]		0.34 [2.68]	-0.08 [-0.32]	0.34
	0.40 [1.36]		0.29 [0.86]	0.38 [3.01]	-0.01 [-0.05]	0.36
10 D/P	0.07 [0.20]	0.62 [2.60]		0.45 [3.05]	-0.11 [-0.45]	0.31
	0.46 [1.75]		0.03 [0.82]	0.30 [1.84]	0.01 [0.02]	0.34
10 ME	-0.01 [-0.02]	0.76 [2.50]		-0.21 [-0.99]	0.01 [0.10]	0.53
	0.46 [1.44]		0.24 [0.71]	0.03 [0.16]	0.22 [1.79]	0.55
25 FF	0.19 [0.91]	0.54 [2.99]		0.32 [2.81]	-0.01 [-0.13]	0.43
	1.06 [5.89]		-0.36 [-1.70]	0.48 [3.85]	0.13 [1.09]	0.45
10 Prior 1-0	0.27 [0.97]	0.88 [2.94]		0.03 [0.11]	0.13 [0.59]	0.27
	0.05 [0.15]		0.61 [1.67]	-0.01 [-0.04]	-0.02 [-0.09]	0.28
10 Prior 12-2	0.33 [1.28]	0.55 [2.06]		-0.57 [-2.26]	-0.62 [-2.74]	0.38
	1.20 [3.31]		-0.46 [-1.14]	-0.54 [-2.36]	-0.36 [-1.60]	0.43
10 Prior 60-13	0.15 [0.63]	0.76 [3.26]		0.33 [1.79]	-0.18 [-0.99]	0.36
	0.78 [2.82]		-0.05 [-0.16]	0.12 [0.70]	-0.04 [-0.22]	0.37
30 Industries	0.04 [0.22]	0.75 [4.76]		0.06 [0.46]	-0.07 [-0.52]	0.20
	0.56 [3.13]		0.15 [0.65]	0.15 [1.12]	0.11 [0.78]	0.24

Table 4.4 Robustness checks

Panel A shows results from Fama-MacBeth regressions when the test assets and/or test periods are randomized. 95% confidence intervals are in curly brackets. Panel B shows results from a bootstrap analysis where portfolio returns are matched randomly with risk factors.

Panel A: Randomization of Test Assets and Test Periods

	Random portfolios	Random periods	Random portfolios and periods
Const.	0.20 {0.08 ; 0.32}	0.17 {-0.17 ; 0.51}	0.20 {-0.17 ; 0.59}
$\hat{\theta}$	0.58 {0.45 ; 0.72}	0.63 {0.40 ; 0.84}	0.58 {0.30 ; 0.87}
HML	0.20 {0.12 ; 0.28}	0.24 {0.02 ; 0.45}	0.20 {-0.03 ; 0.44}
SMB	0.07 {-0.04 ; 0.18}	0.07 {-0.16 ; 0.28}	0.07 {-0.19 ; 0.33}
R^2	0.31 {0.28 ; 0.33}	0.30 {0.28 ; 0.31}	0.31 {0.28 ; 0.34}

Panel B: Bootstrap Analysis

	$\hat{\beta}$	$\bar{\hat{\beta}}$	$\sigma\left(\bar{\hat{\beta}}\right)$	$\left(\hat{\beta}-\bar{\hat{\beta}}\right)\Big/\sigma\left(\bar{\hat{\beta}}\right)$
$\hat{\theta}$	0.66	0.00	0.07	9.43
HML	0.22	-0.00	0.06	3.67
SMB	0.01	0.00	0.05	0.21
R^2	0.29	0.00	0.01	

Appendix Descriptive statistics for the Fama-French risk factors

Descriptive statistics for the three Fama-French risk factors, namely the monthly mean, standard deviation (std), skewness (skew) and kurtosis (kurt). MKTRF denotes the market excess return (over the risk-free rate).

	MKTRF	HML	SMB
Mean	0.64	0.45	0.21
Std	4.55	2.93	2.98
Skew	-0.53	0.74	0.76
Kurt	6.28	8.95	9.63

Chapter 5:
Does professionalism consistently affect portfolio biases?[*]

5.1 Introduction

Participants in financial markets often show biased behavior that reduces their performance (e.g. Barber and Odean, 2000). It may be less expected that not only unsophisticated participants but also professionals are plagued by "biased" behavior as demonstrated by excessive turnover (Dow and Gorton, 1997), home bias (Shiller et al., 1996) and loss aversion (Coval and Shumway, 2005). Professionals' deficits can become so severe that their decisions are even inferior to those of laymen (e.g. Dennis and Strickland, 2002, Glaser et al., 2005, Haigh and List, 2005).[36]

However, professionalism has also proved to be a performance-enhancing factor (e.g. List, 2003, Locke and Mann, 2005, Alevy et al., 2007). Clearly, professionalism is an important determinant of behavior but whether it has a consistent positive impact on decision making in financial markets is not fully clear yet. Accordingly, we provide a new kind of evidence by measuring professionalism in three dimensions and examining the effect of professionalism on three portfolio biases in a broad cross-sectional study. To obtain the necessary data, a survey of about 500 investors has been conducted, covering institutional and individual investors in a uniform way.

The blurry evidence about the impact of professionalism provides a strong challenge to economic reasoning. Markets require rational, i.e. here unbiased, behavior to be efficient. Unbiased behavior is also a crucial element in the increasingly popular models with heterogeneous agents (e.g. De Long et al., 1990). These models assume that one group in the market behaves according to conventional capital market theory, i.e. relies on fundamental information and rational decision-making. This group is usually thought

[*] This chapter is based on a paper with the same title co-authored with Lukas Menkhoff (Leibniz Universität Hannover) and Ulrich Schmidt (University of Kiel).
[36] The list of professionals' biases includes also herding (Sias, 2004), momentum trading (Grinblatt et al., 1995) and overconfidence (Glaser and Weber, 2007). They may even represent noise traders in the market (Dasgupta et al., 2006).

to be made up by professionals whereas laymen, such as individual investors, are typically assumed to belong to the group of noise traders (De Bondt, 1998, Kaniel et al., 2005). If empirical research could not identify significant differences regarding portfolio biases of these two groups this would pose a clear disappointment for models with heterogeneous agents, for the efficient market hypothesis and for the practice of investment management.

Our study differs from earlier research on the impact of professionalism on investor behavior and portfolio biases due to its empirical design. We conduct a survey study with almost 500 respondents which makes four contributions:

A *first* contribution is measuring "professionalism" in a deepened way. We complement the usual distinction between institutional and individual investors[37] by a third, intermediate group, i.e. investment advisors. [38] Moreover, we extend this occupation measure of professionalism by two more dimensions, i.e. experience and knowledge. The impact of experience has been analyzed within groups, such as Feng and Seasholes (2005) or Dorn and Huberman (2005) on individual investors and Greenwood and Nagel (2007) or Menkhoff et al. (2006) on institutional investors.[39] The measure of knowledge has been almost neglected with the exception of Dorn and Huberman (2005) and can hardly be identified without using a survey.

Second, we address the concern voiced that evidence in behavioral finance often seems eclectic (e.g. Shiller, 1999). Accordingly, we examine the impact of professionalism – in its three dimensions and considering controls – on three portfolio biases which can be seen as stylized facts of financial markets, i.e. portfolio churning, home bias and reluctance to loss realization.[40] Further candidates that have been suggested to help our understanding of several behavioral distortions include the wealth of investors (Vissing-

[37] These studies include Shiller and Pound, 1989, who show that institutional investors rely more on fundamental information; Grinblatt and Keloharju, 2000, Barber and Odean, 2007, reveal superior performance of institutional investors; Shapira and Venezia, 2001, find a weaker disposition effect for institutional investors; Cohen et al., 2002, find a more rational response of institutions towards News; see also Glaser et al., 2005, Haigh and List, 2005, introduced above.

[38] Investment advisors are professional in the sense that they work for a financial institution and that they give advice to customers. However, they seem to be less professional on average than institutional investors because of their job profile: their customers are less qualified in financial terms, they have to deal with more clients, they do not have access to first hand information (but get financial information from the bank's headquarter) and they earn usually a lower salary than institutional investors.

[39] An important role of experience has been found in other settings too, such as the field study of List (2003) and the experiment of Loomes et al. (2003).

Jørgensen, 2003), their perceived competence (Graham et al., 2005), their risk aversion (Dorn and Huberman, 2005) or their experience (Menkhoff et al., 2006). These studies, however, rely on information from either individual or institutional investors and accordingly do not focus on the impact of professionalism.

A *third* contribution is extracting information about the impact of professionalism which is undistorted by other determinants of investment decisions, such as different incentives or transaction costs. We know that institutional investors have higher turnover than individual investors (e.g. Carhart, 1997), we know that institutional investors invest less at home (Grinblatt and Keloharju, 2001) and that they sell assets easier conditional on capital losses (Grinblatt and Keloharju, 2001a). However, these studies compare institutionals' job behavior with individuals' private behavior. Despite their appeal in relying on "hard" trading figures, this kind of studies faces the disadvantage that institutional investors' decisions are known to be determined by transaction costs and incentives in addition to professionalism.[41] Thus, higher turnover or less home bias may be the outcome of lower transaction costs, high turnover may be due to portfolio churning (Dow and Gorton, 1997) and willingness to sell may be driven by "window dressing" as well (Lakonishok et al., 1991).

As *fourth* contribution to the literature, the survey allows to consider the most important determinants being identified before as controls. Some of these variables cannot be compiled at all without conducting a survey.[42] We discuss the impact of these variables, such as age, the degree of education, the seniority of position reached, when we explain portfolio biases (section 5.3).

Our study provides three main findings: first, we establish that professionalism – in each of its three dimensions – is a statistically significant and economically meaningful characteristic of investors that unambiguously reduces the three portfolio biases considered here. This suggests that professionalism may be one of the underlying factors helping to better structure behavioral finance findings. Second, the novel joint analysis of three measures of professionalism shows that they are not necessarily correlated to

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[40] There is clear evidence that these biases reduce performance as e.g. Barber and Odean (2000) show for high turnover, Lewis (1999) demonstrates for home bias and Odean (1998) proves for reluctance to loss aversion.

[41] This is of course no argument against the analysis of (institutional investors') trading data but in favor of using survey data as complementary evidence.

[42] Accordingly, questionnaire surveys have become a standard research tool when information is required that cannot be drawn from other sources (see e.g. Blinder, 2000, on central banks' views about credibility, surveys on investors' beliefs as for example Shiller and Pound, 1989, or surveys on investors' price expectations, such as Frankel and Froot, 1987).

each other. Thus professionalism has different dimensions; interestingly, investment advisors – although professional in a sense – do not behave similar to the most professional institutional investors. This emphasizes that the empirical measures of professionalism deserve careful attention. Third, the survey approach reveals – possibly for the first time – investment behavior of professionals in their private domain. This generates the insight that institutional investors trade *less* than individual investors in their private accounts, although their turnover is *higher* when taking their behavior in the job. Accordingly, surveys provide useful complementary evidence in identifying the impact of professionalism.

The chapter proceeds in the following way. Section 5.2 gives information on the data generated, including a discussion of reliability and representativeness. The core of the analysis is laid out in section 5.3, where we perform regression analyses to learn about the impact of professionalism on portfolio churning, home bias and reluctance to loss realization. Conclusions are presented in section 5.4.

5.2 Data

This section shows that the data set is useful to serve our research purpose. The data are by and large reliable (section 5.2.1) and they are representative for relevant investor groups (section 5.2.2). We find portfolio biases in the data (section 5.2.3), relate our three measures of professionalism to each other (section 5.2.4) and describe participants' behavior and beliefs (section 5.2.5).

5.2.1 Data compilation

The data employed here have been compiled to examine our research questions. Data come from an online survey of German investors conducted from 4th to 11th November 2004 in cooperation with sentix®.

The latter is a large German online platform where registered individual and institutional investors give their expectations concerning relevant financial and economic indicators and asset prices on a weekly basis. As a reward for their participation, users can view results of the surveys and market analyses based on these surveys provided by the operators of sentix. Thus, sentix users do not represent average but highly committed individual investors.[43] Moreover, due to their commitment, we expect investors to understand the questionnaire well and to respond carefully. We used this platform to distribute our own survey questionnaire and received a total of 497 responses during the above-mentioned week in November 2004. The absolute response is thus in the same dimension as the number of active participants during the first two weeks in November 2004 (475 and 509 respondents respectively).

Since the survey is anonymous we asked participants to indicate whether they are individual investors, investment advisors or institutional investors. Our 497 responses are made up of 75 institutional investors, 78 investment advisors and 344 individual investors. This self-indication of respondents can be cross-checked with the database of sentix®, which contains information about the affiliation of investors with professional financial institutions such as banks, asset managers, or insurance companies; so we can be sure that participants did not indicate themselves as professionals although they are not.

Often-voiced concerns regarding survey data are that participants do not fully understand all questions, that they answer strategically or that they randomly answer without thinking about the questions. However, none of these objections seems to be a problem in this online survey. First, we conducted a pretest to ensure understandable wording and relevant questions. Nevertheless, investors did not have to answer all questions if they did not like to or if they did not understand the questions. Second, since the questionnaire was anonymous and announced to be used for academic purposes only, there does not seem to be an incentive for strategic answering. Strategies aiming for a distortion of the overall level of answers were useless ex ante due to the large number of participants addressed; this disincentive has proved to be credible because of the many responses realized. Third, since participants in our survey are registered users of sentix® and take part in the weekly questionnaire voluntarily, it can be expected that they are highly interested in financial market research and have an intrinsic motivation to answer correctly.

Overall, the data seem to be as reliable as can be expected for a survey questionnaire. Further insights can be gained from analyzing participants attributes.

[43] The online survey among registered users is anonymous and voluntary. Registration is necessary to ensure prudent behavior at the platform and is not restricted otherwise. More details can be inferred via www.sentix.de.

5.2.2 Participants' objective attributes

This section shows objective attributes of participants, such as age, education etc., which allows comparisons with other data sets describing investors. We find that our sample is by and large representative for our target investor groups.

The average investor of our survey is about 40 years old, has roughly 12 years of investment experience, has earned a university degree, is male, occupies a senior position, privately invests a securities volume of about 250 thousand Euros and holds an equity share of 40%. Therefore, we have a sample of well-qualified investors (details are provided in **Appendix 1**).[44]

Investor groups differ in some characteristics to a statistically significant degree. Individual investors are older than the two other groups, have the shortest investment experience (despite their highest age) and occupy most senior positions on average (possibly reflecting their higher age). Investment advisors' experience is different from institutional investors as there are more persons with shorter experience as well as more persons with very long experience. Finally, institutional investors are most wealthy – indicated by the investors' private portfolio volume – as about a quarter of them own a portfolio of more than one million Euros (significant at the 10% level).[45]

Many of these attributes have been compiled in earlier survey studies on institutional investors in Germany and show that our sample is similar to them (see Menkhoff et al., 2006 and sources therein). Regarding individual investors, demographic information about survey respondents from a June 2000 survey of a German online broker's clients (Dorn and Huberman, 2005) matches our data quite well; data is also similar to the UBS/Gallup participants studied by Graham et al. (2005). When we compare our individual investors, however, with the total investor population in Germany, it becomes obvious that our sample is distorted towards more qualified individual investors (see data in Dorn and Huberman, 2005).

In summary, our sample of investors in Germany is quite representative of institutional investors but reflects characteristics of highly-qualified individual investors.

[44] We also use these personal characteristics as control variables because they are related to investment behavior (e.g. Agnew et al., 2003, Vissing-Jørgensen, 2003, Graham et al., 2005, Menkhoff et al., 2006, Karlsson and Nordén, 2007).

[45] Unfortunately, the low variance of "gender" in our sample does not allow us to include this item in any regression.

Thus, the difference between groups is narrower than in the full population which heightens the stakes to find any effect by professionalism on investment behavior.

5.2.3 Participants' portfolio biases

In addition to participants' objective attributes – covered in section 5.2.2 – we make use of the survey instrument to learn more about investors in the following sections. We do indeed find portfolio biases, i.e. too high portfolio turnover, too much home investment and too strong reluctance to loss realization.

The exact questions on portfolio turnover, domestic investment share and reluctance to loss realizations are summarized – as are all further survey questions and statements – in **Table 5.1**. For our measure of portfolio churning we relate portfolio turnover to portfolio volume (see item 1 in Table 5.1). Participants had to choose between four categories, where long-term buy and hold investors would select category 1 or possibly 2, whereas investors with a clear tendency towards portfolio churning would fall into categories 3 and 4 accordingly. **Figure 5.1** gives the frequency distribution, showing that only about 10% of investors belong to the category with very low turnover and another 30% to the next category. 60% of our investors, however, have a turnover rate of more than 25%, 40% are even above 50%. Figures for the groups of investors, i.e. institutional investors, investment advisors and individual investors show that 30%, 40% and 43% respectively have an annual turnover of more than 50%. Assuming a rather conservative midpoint of 75% for the highest turnover category, the mean turnover rates for these three investor groups are roughly 38%, 44% and 45%.[46]

We will use these four categories of increasingly higher turnover as our measure of portfolio churning. We are aware that this is an imprecise measure because there may be very different motivations for transactions, such as pure liquidity motives or private information. However, the same criticism would also apply to a statistical figure being derived from bank accounts and is thus a price that has to be paid when analyzing turnover.

[46] A typical turnover figure for institutional investors is about 70 to 80% (e.g. Carhart, 1997). Turnover figures for individual investors seem to depend on investor and portfolio type. For example, investors with an online broker show very high turnover, such as roughly 75% p.a. (Barber and Odean, 2000, p.775) for a US case, contrasted by the figure from US single 401(k) pension investments with turnover of 16% (Agnew et al., 2003, p.194).

To measure our second portfolio bias of interest, i.e. home bias, we ask participants to allocate an amount of 10,000 € to five world regions (see item 2 in Table 5.1). The share being invested in Germany, i.e. in the domestic country, is the figure of interest.[47] **Figure 5.2** gives the frequency distribution of preferred domestic investment share. One can directly infer that only about 4% of these investors prefer a German investment share of up to 5% and less than 8% would invest up to 10% in Germany. The remaining 92% would thus invest 10% and more of their portfolio in the domestic country. The mean value of home investment is 29.6% and the median is still 20%.[48] The figures for the groups of institutional investors, investment advisors and individual investors are 19.2 (17.5), 31.8 (25.0) and 31.5 (20.0) for the mean (median) respectively.

This preference contrasts with Germany's share in world stock market capitalization of 3-5% only, depending on the type of securities considered. So, investment shares of 10% and more, as they characterize the preferences of about 90% of investors, can be qualified as home bias. Accordingly, we simply take the share being invested in Germany – grouped into six categories – as the degree of home bias.[49]

Finally, to measure our third portfolio bias, i.e. the reluctance to loss realization, we take the degree of approval to the statement that investors usually wait for a price recovery instead of selling those securities in case of loss positions (see item 3 in Table 5.1). Participants could answer with one of six categories, ranging from complete approval to complete disapproval. In theory, there is no reason to wait for a price recovery which is simply an orientation on past prices. In reality, however, the frequency distribution of answers in **Figure 5.3** shows that investors say to behave reluctantly to realize losses: 30% of the respondents rather agree with the statement and less than 25% completely disapprove. The figure also directly visualizes the difference between investor

[47] This measure of preferred home investment is thus undistorted by any regulatory requirements that effectively limit for example pension funds to invest abroad.
[48] When one analyzes the share of home investment in absolute terms, the mean value of 30% seems rather low compared to earlier measures given in the literature (Lewis, 1999, Flavin and Wickens, 2006, Lütje and Menkhoff, 2007). A reason may be that our sample is biased towards more sophisticated investors as indicators of education, experience, equity share and volume reveal.
[49] Two qualifications have to be made here: First, Germany's share in bond markets is higher at about up to 7%. So, Germany's total share in world market capitalization may be up to 5%. Second, all investors who allocate 3-5% to Germany do not show any home bias. These qualifications are considered in our analysis, however, as we categorize the degree of home bias into six groups, starting with all investors in the same group who allocate less than 10% to the German market.

groups: whereas 40% of individual investors and even 43% of investment advisors rather agree with the statement, only 28% of institutional investors do so.

5.2.4 Three measures of professionalism

This section introduces our third measure of professionalism, which is related to the two other measures (see section 5.2.2) but not the same. Nevertheless, all three measures of professionalism are inversely related to both portfolio biases.

Whereas the competent occupation of investors and their investment experience do not need further elaboration as measures of professionalism, our third measure does. The fourth item in Table 5.2 introduces this knowledge-based measure of professionalism. The question in this respect asks investors to give a 90%-interval within which they expect the DAX to fall over the next one-month period. Experts should give a more precise response. In particular, they should be aware that volatility can be predicted to some degree. Therefore, the degree of knowledge being incorporated in the answers can be identified by comparing the forecast given with the forecast generated by a standard GARCH (1,1) model. Thus, the variable "worse variance forecast" measures the absolute deviation of the investor's forecast from the model-generated forecast (as a percentage share and adjusted for the DAX point forecast), i.e. it captures investors' absolute variance forecast "errors" (Table 5.2, item 4). Therefore a higher value of this spread measures too large or too low interval forecasts and thus indicates poor market knowledge.

Interestingly, the knowledge measure of professionalism is not related to professional occupation in a statistically significant manner and thus provides a new aspect of professionalism (see **Table 5.2**). More knowledgeable investors, however, tend to be more experienced (at a 6% level of significance only). Finally, institutional investors are more experienced than others. So the "worse variance variable" measures a different dimension of professionalism than the two other measures do. These other measures, occupation and experience, are closely related but not identical. Accordingly, these measures of professionalism will not necessarily have the same relation to further variables.

As we are interested in three portfolio biases, we examine – as a first approximation – correlations of professionalism measures with these biases. Table 5.2 shows that the biases are not significantly correlated to each other. Furthermore, the nine coefficients of correlation between three biases and three professionalism measures are not all statistically significant: occupation and experience seem to work unanimously against all three biases; knowledge does so against home bias only, whereas its relation to portfolio churning and reluctance to realize losses has the "correct" sign but fails to be significant.

We have thus gained a first insight into the relations of interest, which will be tested more appropriately in a regression approach in section 5.3. This requires a more complete set of possibly relevant determinants of portfolio biases, which is discussed next.

5.2.5 Participants' beliefs

Portfolio biases may be influenced by further determinants which we introduce in three groups.

To control the importance of professionalism in explaining portfolio biases, three variables are included which are related to decision making in financial markets (see Table 5.1, items 5 - 7). First, the general attitude regarding risk aversion in professional investment decisions is asked for (see Dorn and Huberman, 2005). Second, it has been shown that institutional investors are less affected by the detrimental disposition effect than individual investors (Shapira and Venezia, 2001). Including a variable capturing the disposition effect (see Shefrin and Statman, 1985, Weber and Camerer, 1998) thus allows disentangling the effect of a behavioral distortion from a pure professional effect. Third, a long-term forecasting horizon when making investment decisions may influence behavior and is thus elicited (Klos et al., 2005). Investors in our survey classify themselves as being somewhat less risk averse than the hypothetical average investor (detailed responses are documented in **Appendix 2**). Their self-classification towards a possible disposition effect is well-balanced within the range of possible answers, with institutional investors having a lower degree than individual investors. Finally, forecasting horizon in investment decisions is distributed around "2-6 months" as the median and modus; individual investors have the relatively shortest horizon.

The following two items 8 and 9 in Table 5.1 address the issue of appropriate self-evaluation which is important as overconfidence reduces performance (Barber and Odean, 2000). As expected from earlier studies, almost all investors in our sample think of themselves as having better performance and information than other investors. We understand the relative performance question (item 8) as a conventional “better-than-average” measure of overconfidence (Glaser and Weber, 2007). Somewhat different from this, the question on a relative level of information (item 9) also captures perceived knowledge. The perception of being more knowledgeable is a core element of the Graham et al. (2005, p. 9) understanding of competence. As a cautious warning, we notice the benchmark of self-evaluation, which is here defined as “other investors”. It may well be that our sample is not so much overconfident but indeed superior to other investors. This applies in particular to the significant differences between more confident institutional and less confident individual investors, whereas the high self-evaluation of investment advisors is more surprising.

The last two items 10 and 11, local information advantage and return optimism, are relevant as determinants of home bias only (see French and Poterba, 1991). Obviously, the belief in a domestic information advantage is not so strong because answers tend slightly towards contradiction than approval. Interestingly, individual investors believe least in a domestic information advantage and investment advisors most.[50] In item 11, investors are asked to give their return expectation for Germany's leading stock market index, the DAX, because a higher share of investments at home would make sense if return optimism were higher too. However, return expectations of respondents are distributed around zero. Note that differences *within* groups are large whereas differences *between* the three groups are not statistically significant. Tentatively, home bias is positively related to return optimism in our sample, reflecting the fact that home bias has been found to be related to unrealistic return optimism among institutional investors (Shiller et al., 1996, Strong and Xu, 2003).

Up to this point of analysis, lessons from descriptive statistics tentatively confirm earlier findings and indicate that professionalism may lead to lower portfolio biases. The complex relations give a strong warning, however, not to rely too early on univariate analyses but to perform multivariate regressions. This is done in the following section.

[50] Theoretical studies (e.g. Gehrig, 1993) and empirical works (e.g. Coval and Moskowitz, 2001, for fund managers and Ivkovic and Weisbenner, 2005, for individual investors) have shown that a local information advantage may be real, although others find contradictory evidence (e.g. Huberman, 2001, for individual investors, Lütje and Menkhoff, 2007, for institutional investors).

5.3 Regression analysis

We find that all three measures of professionalism are robust determinants of portfolio biases. These measures hold simultaneously, indicating the different aspects of professionalism being captured. We present results for the three portfolio biases in sections 5.3.1 to 5.3.3. Finally, we compare these results in section 5.3.4.

5.3.1 Results for portfolio churning

We employ ordered logit regressions to account for the ordered, discrete nature of our response variable "portfolio churning". All statistical inference here and in the following models is based on 250 bootstrap replications.

In a first regression, all relevant variables that have been discussed in section 5.2 are included. **Table 5.3** gives results for various specifications in explaining turnover. We start with a regression including all possibly relevant variables (column 1). As can be seen, institutional investors have lower turnover than the two other groups, i.e. investment advisors and individual investors. More experienced investors have lower turnover too and a worse variance forecast is related to higher turnover. Thus each of the three professionalism variables has an "economically positive" sign and is statistically significant. Within the group of personal characteristics, two variables are significant here, i.e. age and volume: younger and wealthier investors have higher turnover.

Coming to the group of control variables, we find that less risk-averse investors, investors with a shorter forecasting horizon and confident investors, who believe to perform better, show higher turnover. If we leave out only the variable "less performance than others" (see column 2) the variable "less information than others" attracts some of the former explanatory power but does not become significant. Interestingly, the disposition effect is not important in explaining portfolio churning. These results are very similar to those found in Dorn and Huberman (2005, Table 9).[51]

[51] They also find experience, knowledge (differently defined than here), wealth, risk aversion and overconfidence (in their study: perceived own knowledge relative to others) to explain turnover as we do. Moreover, they find men to exhibit more turnover, a variable which cannot be used in our sample, whereas we find occupation and forecasting horizon to be significant, two variables that are not included in Dorn and Huberman (2005). The only variable that comes out somewhat differently is age, which loses significance in Dorn and Huberman (2005) when they use a larger set of controls.

As further robustness checks, we leave out three insignificant variables and also include only one of the three professionalism measures at a time (columns 3 - 5). Results are not too much affected. In particular, the professionalism measures are always statistically significant. A last regression is presented in column 6, where all insignificant variables are excluded, among them the portfolio volume which has turned insignificant. Again, professionalism keeps its high importance.

An analysis of marginal effects at variables' medians for the last specification (6) in Table 5.3 highlights the economic significance of the professionalism variables. Being an institutional investor increases the probability of being in one of the "low turnover categories" (i.e. x ≤ 25% p.a.) – which has an unconditional probability of about 25% – by 12.5 percentage points[52] and raising the experience level by three categories increases the probability of a low turnover by more than 6 percentage points (detailed results are presented in **Appendix 3**, Panel A). A one percent increase in the variance forecast error lowers the probability of having a low turnover by 0.7 percentage points.

5.3.2 Results for home bias

This section matches the above finding: all three measures of professionalism robustly indicate that more professional investors are less subject to home bias.

In parallel to the previous section, we estimate ordered logit regressions. The dependent variable is a categorical transformation of our domestic investment variable, since this original variable lies in the interval [0,1] and is thus not well captured by standard linear regression models. We make use of the ordered nature of our data and form six different categories: [0,10), [10,30), [30,50), [50,70), [70,90), [90,100]. The two smaller categories in the left-hand and right-hand margins are used to capture the observed extreme realizations of home bias. As a robustness check we also employ censored linear regressions where the censoring takes place at an investment share of zero and one hundred percent.

Results of the ordered logit model are given in **Table 5.4**. We start – as we did in section 5.3.1 – with a regression including all possibly relevant variables (column 1). As can be seen, the three measures of professionalism are statistically highly significant: institutional investors have a lower home bias than the two other groups, i.e. in-

[52] This can be seen by adding the first two entries in the table corresponding to the "institutional investors" variable (i.e. 0.035 + 0.090 = 0.125 = 12.5 %).

vestment advisors and individual investors. More experienced investors have a lower home bias and a worse variance forecast is related to more home bias. Coming to the group of personal characteristics, we find that older investors prefer home assets compared to younger ones. Whereas this determinant has been found by Karlsson and Nordén (2007) and Lütje and Menkhoff (2007) before, further determinants that have been claimed by Karlsson and Nordén (2007) are not significant in the extended approach here. This refers to share of equities, higher wealth and also to better education and more senior position.[53]

Next, let us discuss the group of further controls to single out the effect from professionalism. One can recognize in this regression that the degree of general risk aversion is not important. By contrast, a smaller disposition reduces home bias, independent of the professionalism of the investor. We see this as further evidence for the disturbing power of the disposition effect in financial decision making. Moreover, the variable longer forecasting horizon has some influence in reducing home bias but is significant at the 10% level in this specification only.

Finally, we have added two variables specifically to explain high domestic investments. These variables – capturing information/transaction costs and return optimism – are among the best-established determinants of home bias according to earlier studies and it is thus reassuring that they also hold here.[54] This is despite the different method for data compilation, the questionnaire survey, and despite many more control variables that are included here than before.

As robustness checks we test further specifications. First, we leave out four statistically insignificant variables which have had less importance in earlier studies; this does not affect results (Table 5.4, column 2). Second, due to the focus on professionalism, we run a set of further regressions where the measures of professionalism are considered one after the other. The results presented in columns 3 - 5 in Table 5.4 show that each of the professionalism measures keeps its sign and significance. The same applies to the main other determinants. Third, we include only statistically significant variables in the regression. Column 6 shows that the variable forecasting horizon then loses significance but that all three measures of professionalism remain. Fourth, column 7 esti-

[53] In order to come closer to a replication of Karlsson and Nordén (2007), we have run a regression explaining individual investors' home bias solely by these personal characteristics. We find that in this case higher age and also investment volume (as a proxy for wealth) significantly reduce home bias.

mates the specification of column 6 with a censored linear regression – again, findings are confirmed.

The professionalism variables are also significant in economic terms (see Appendix 3, Panel B). Marginal effects evaluated at variables' medians for specification (6) in Table 5.4 reveal that being an institutional investor increases the probability of being in the "low home bias" categories (w≤30%) – which has an unconditional probability of about 60% – by more than 21 percentage points. Increasing the level of experience by e.g. three categories increases the probability of being in the low home bias categories by more than 12 percentage points whereas increasing the variance forecast error by one percent decreases the low home bias probability by more than one percentage point (a similar picture emerges from the effects in the censored linear models).

5.3.3 Results for reluctance to loss realization

In analogy to the last two sections we find for all three measures of professionalism that more professional investors are less reluctant to realize losses in their portfolios.

The variable "reluctance to loss realization" has six categories and is thus analyzed in an ordered logit approach. **Table 5.5** gives results for similar specification as for the other biases analyzed before. What stands out is that there are less significant variables than in the earlier regressions. Interestingly, the three professionalism variables belong to this group. By contrast, personal characteristics do not seem to be relevant here. Among the control variables, having less disposition effect and a longer forecasting horizon reduce the portfolio bias. This result holds through all six specifications with one slight qualification in specification (5) where the knowledge measure of professionalism marginally falls out of the 5% significance interval.

As the reluctance to loss realization can be seen and is often analyzed as one element of the disposition effect (e.g. Odean, 1998), one may question whether the disposition effect variable is exogenous. However, eliminating it from an earlier regression (column 6) does not qualitatively change the picture as the result in column 7 shows (this also holds for the other specifications and regressions in Tables 5.3 and 5.4).

[54] One may question the meaning of the information advantage variable as it is measured as a subjective assessment and does not necessarily mean that an information advantage exists.

The marginal effects for the reluctance to loss realization variable are based on the last specification (6) in Table 5.5 (see Appendix 3, Panel C). Being an institutional investor decreases the probability of being in one of the three categories of low reluctance by 13.4 percentage points. This is clearly of economic significance since these three categories of low reluctance have an unconditional probability of 39%. Similarly, increasing experience by three categories increases the probability of low reluctance by almost 11 percentage points. Finally, increasing knowledge (as measured by the variance forecast) by one percent increases the probability of having a low reluctance to loss realization by more than one percentage point.

5.3.4 Comparing the three portfolio biases

A comparative analysis of the determinants of portfolio churning, home bias and reluctance to loss realization shows that these are three different problems in investment behavior. However, there is one common lesson: professionalism reduces the biases.

Going through the regressions just discussed in sections 5.3.1 to 5.3.3, the three measures of professionalism are the only variables that are always significant and keep their sign. As all other variables enter either only one or two regressions or change sign (the age variable), we understand that the three portfolio biases are different phenomena. Portfolio churning is – beyond professionalism – driven by age, risk aversion, forecasting horizon and a perceived better performance than others. Here, one may recognize a driving force in tentatively overconfident, risk-taking activism. By contrast, home bias is – beyond professionalism, information advantage and return optimism – driven by higher age and more disposition effect. Age can be understood as proxy of a particular kind of higher risk aversion and the disposition effect could be seen as behavior to avoid (possibly wrong) decisions. Finally, reluctance to loss realization is – beyond professionalism – only influenced by a higher disposition effect (which is related to the endogenous variable) and by a shorter forecasting horizon. In a sense, the three portfolio biases are thus driven by rather divergent motivations.

These different origins of portfolio churning, home bias and reluctance to loss realization make the result of professionalism even more interesting: in the case of portfolio churning professionalism helps to reduce unjustified activism, in the case of home bias professionalism helps to overcome unjustified risk aversion and in the case of reluctance to loss realization professionalism helps to cut losses early.

5.4 Conclusions

Recent studies have found that professionals do not necessarily perform better in (financial) markets than laymen. Therefore, it is not clear ex ante whether more professional investors show less portfolio biases which would be important for both market efficiency and the investment management industry.

Earlier studies on the impact of professionalism on portfolio biases are characterized by limitations in design which we want to overcome to some extent. Therefore, we have conducted a new survey and asked about 500 German investors via a questionnaire about their behavior, objective attributes, and beliefs. This effort generates information on portfolio behavior that was not available before: it compares investors with different degree of professionalism in a uniform way, i.e. regarding their private investment decisions, it allows to test the impact of three dimensions of professionalism in the same regressions and it is possible to examine the impact on three portfolio biases in a single framework, including the consideration of various relevant control variables.

We find clear evidence that professionalism reduces the portfolio biases of portfolio churning, home bias, and reluctance to loss realization. It is only professionalism measures that keep their significance and sign in explaining these portfolio biases. Other variables, however, are either not significant (including wealth of investors), or change sign (the age variable) or are significant in only one or two of the three cases. Second, we find that all of the three dimensions of professionalism are important because each of them adds an additional piece of explanatory power to the regressions. Moreover, investment advisors – although clearly a professional group – behave more like advanced laymen than as institutional investors. Third, the survey approach makes a further difference as it shows that institutional investors have lower turnover in their private portfolios than individual investors, although institutionals show much higher turnover in their job-related trading.

Table 5.1 Further survey questions and statements

	Item	Question, statement	Categories
1.	Higher turnover	What is your annual turnover (sum of buy and sell transaction volume) relative to the total volume of your portfolio?	4 categories (1 = <10%, 2 = 10-25%, 3 = 25-50%, 4 = >50%).
2.	More home bias	Please allocate an amount of 10,000 € on the following regions so that shares add up to 100 percent. 5 regions: Germany, Europe (ex Germany), USA and Canada, Asia, Emerging Markets.	In percent between 0 and 100.
3.	Less reluctance to loss realization	I generally wait for a price recovery of a loss position, instead of selling this position.	6 categories from "complete approval" (coded as 1) to "complete disapproval" (coded as 6)
4.	Worse variance forecast	Please give a range within which the index will fall with a probability of 90%.	Absolute difference between the width of the range divided by the individual forecast and the width of a GARCH(1,1) forecast divided by the point forecast.
5.	Less risk averse	Please classify your personal risk taking: With respect to professional investment decisions, I mostly act…	6 categories from "very risk averse" (coded as 1) to "little risk averse" (coded as 6)
6.	Less disposition effect	I prefer to take profits when I am confronted with unexpected liquidity demands.	See item 3.
7.	Longer forecasting horizon	What is your typical personal forecasting horizon when making investment decisions?	5 categories from "Days" (coded as 1), "Weeks", 2-6 Months", "6-12 Months" to "Years" (coded as 5)
8.	Less performance than others	How good is your investment performance relative to other investors?	7 categories from "much better" (coded as 1) to "much worse" (coded as 7).
9.	Less information than others	How high is the degree of your information relative to other investors?	7 categories from "much better" (coded as 1) to "much worse" (coded as 7).
10.	Less domestic information advantage	As a domestic investor I benefit from better information compared to foreign market players.	See item 3.
11.	Higher Dax optimism	Please estimate the development of the DAX within the next month.	Point forecast (converted into return forecast).

Figure 5.1 Distribution of annual portfolio turnover
This figure shows the distribution of annual portfolio turnover (x) for all investors in the left panel. Bars show the percentage response (LHS) in a given interval (x-axis). The solid line shows the cumulative percentage response (RHS). The right panel shows percentage responses separately for the three investor groups in a given percentage interval (x-axis).

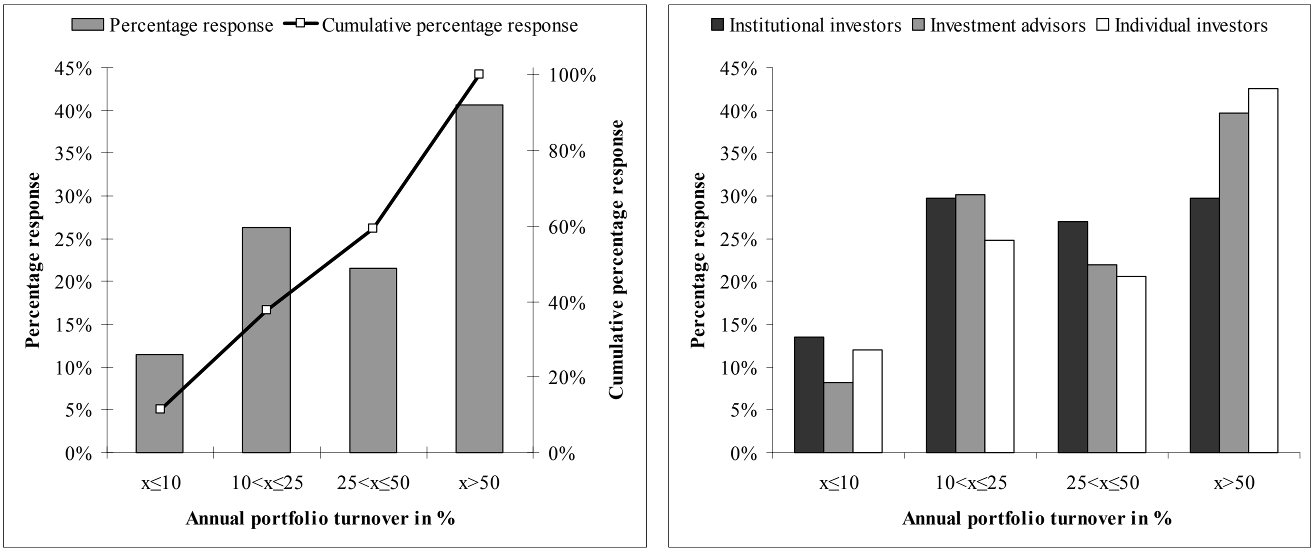

Figure 5.2 Distribution of the share of investment in domestic stocks
This figure shows the distribution of the share of investment in domestic stocks (w) for all investors in the left panel. Bars show the percentage response (LHS) in a given 5% interval shown on the x-axis. The solid line shows the cumulative percentage response (RHS). The right panel shows percentage responses separately for the three investor groups in a given percentage interval (x-axis).

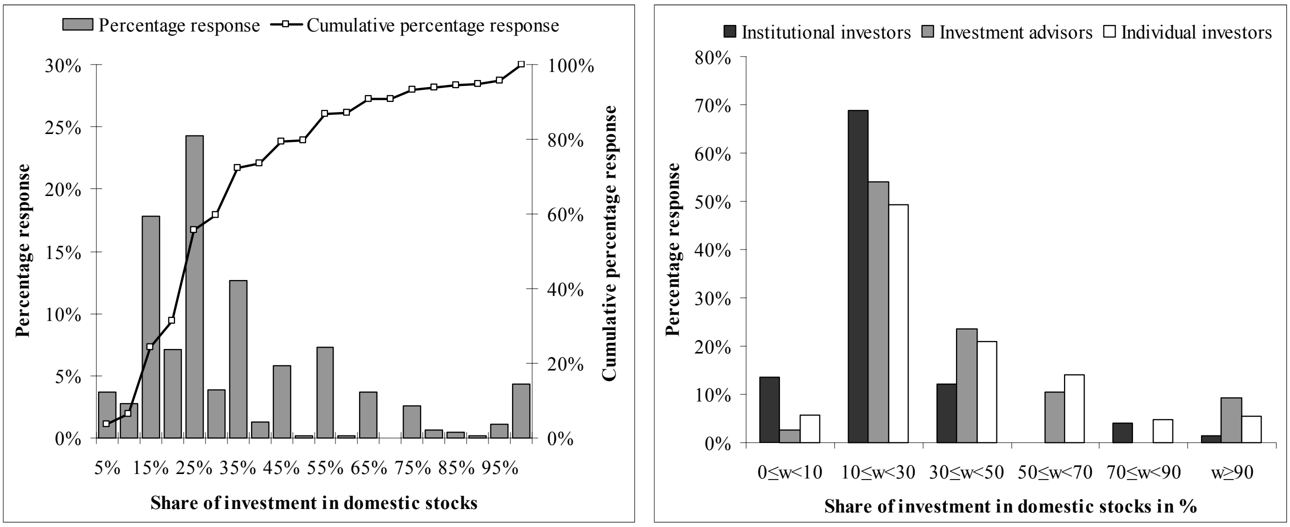

Figure 5.3 Distribution of the reluctance to loss realization
This figure shows the distribution of the reluctance to loss realization for all investors in the left panel. Bars show the percentage response (LHS) in a given approval category (x-axis). The solid line shows the cumulative percentage response (RHS). The right panel shows percentage responses separately for the three investor groups in a given approval category (x-axis).

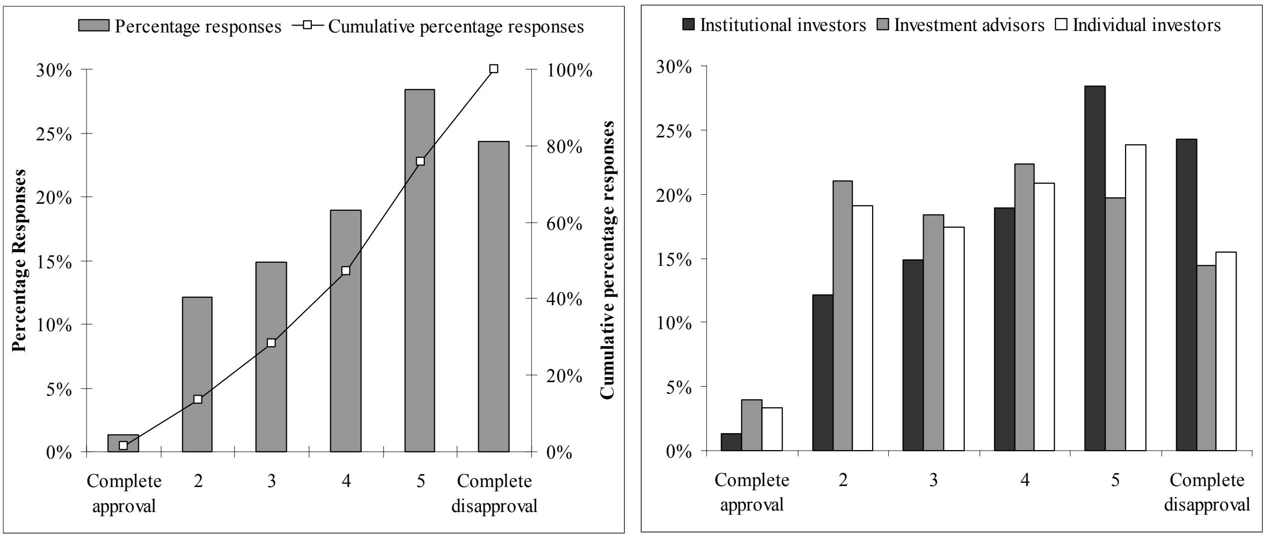

Table 5.2 Correlation of measures of professionalism
This table shows rank correlation coefficients of professionalism measures with portfolio biases. Stars refer to a significance level of: **: 0.01, *: 0.05.

	Institutional investors	Investment advisors	More experienced	Worse variance forecast	More Home Bias	Higher turnover
Institutional investors	1.00					
Investment advisors		1.00				
More experienced	0.12 *(0.01)	0.14 **(0.00)	1.00			
Worse variance forecast	-0.02 (0.63)	-0.01 (0.92)	-0.09 (0.06)	1.00		
More Home Bias	-0.22 **(0.00)	0.06 (0.21)	-0.12 *(0.01)	0.07 (0.12)	1.00	
Higher turnover	-0.10 *(0.03)	0.00 (0.95)	-0.23 **(0.00)	0.06 (0.19)	0.07 (0.15)	1.00
Less reluctance to loss realization	0.12 **(0.01)	-0.06 (0.23)	0.18 **(0.00)	-0.14 **(0.00)	-0.02 (0.65)	-0.05 (0.29)

Table 5.3 Determinants of (higher) turnover

All p-values are based on a bootstrap with 250 replications for the respective specification. Bold numbers represent coefficient estimates that are significant at least on the level of five percent.

Dependent variable: turnover (4 categories)	(1)	(2)	(3)	(4)	(5)	(6)
Institutional investors	**-0.694** **(0.020)**	**-0.650** **(0.026)**	**-0.782** **(0.005)**			**-0.608** **(0.023)**
Investment advisors	-0.384 (0.189)	-0.242 (0.388)	-0.515 (0.061)			
More experienced	**-0.162** **(0.027)**	-0.137 (0.065)		**-0.195** **(0.007)**		**-0.157** **(0.030)**
Worse variance forecast	**4.749** **(0.004)**	**4.56** **(0.004)**			**4.472** **(0.004)**	**4.241** **(0.007)**
Higher age	**-0.282** **(0.002)**	**-0.309** **(0.001)**	**-0.302** **(0.000)**	**-0.172** **(0.040)**	**-0.259** **(0.001)**	**-0.204** **(0.017)**
University degree	-0.219 (0.318)	-0.178 (0.412)				
More senior	0.225 (0.308)	0.239 (0.269)				
Higher share of equities	0.004 (0.228)	0.003 (0.342)	0.004 (0.183)	0.004 (0.186)	0.004 (0.214)	
More volume	**0.177** **(0.019)**	**0.218** **(0.004)**	0.104 (0.155)	0.151 (0.053)	0.097 (0.191)	
Less risk averse	**0.396** **(0.000)**	**0.379** **(0.000)**	**0.413** **(0.000)**	**0.400** **(0.000)**	**0.388** **(0.000)**	**0.436** **(0.000)**
Less disposition effect	-0.007 (0.927)	0.064 (0.353)	-0.003 (0.096)	0.002 (0.782)	0.002 (0.975)	
Longer forecasting horizon	**-0.562** **(0.000)**	**-0.571** **(0.000)**	**-0.584** **(0.000)**	**-0.564** **(0.000)**	**-0.603** **(0.000)**	**-0.547** **(0.000)**
Less performance than others	**-0.373** **(0.000)**		**-0.345** **(0.000)**	**-0.310** **(0.000)**	**-0.275** **(0.001)**	**-0.347** **(0.000)**
Less information than others	0.028 (0.775)	-0.138 (0.127)				
Constant 1	-4.711	-3.326	-4.284	-4.138	-3.610	-4.096
Constant 2	-2.836	-1.497	-2.422	-2.280	-1.763	-2.213
Constant 3	-1.656	-0.355	-1.274	-1.128	-0.617	-1.060
LRT (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.133	0.118	0.124	0.121	0.118	0.128

Table 5.4 Determinants of (more) home bias

Dependent variable: home bias (6 categories†)	(1)	(2)	(3)	(4)	(5)	(6)	(7)‡
Institutional investors	**-0.887** **(0.003)**	**-0.882** **(0.003)**	**-1.047** **(0.000)**			**-1.041** **(0.000)**	**-9.747** **(0.000)**
Investment advisors	0.345 (0.216)	0.306 (0.251)	0.066 (0.793)				
More experienced	**-0.220** **(0.002)**	**-0.202** **(0.003)**		**-0.257** **(0.000)**		**-0.183** **(0.002)**	**-2.282** **(0.000)**
Worse variance forecast	**5.434** **(0.008)**	**4.923** **(0.014)**			**5.094** **(0.011)**	**4.550** **(0.022)**	**0.849** **(0.005)**
Higher age	**0.309** **(0.002)**	**0.271** **(0.005)**	0.153 (0.077)	**0.308** **(0.001)**	**0.203** **(0.015)**	**0.232** **(0.010)**	**3.295** **(0.007)**
University degree	0.073 (0.714)						
More senior	0.109 (0.633)						
Higher share of equities	0.001 (0.654)	0.002 (0.469)	0.003 (0.409)	0.003 (0.345)	0.003 (0.345)		
More volume	-0.000 (0.996)	0.004 (0.0958	-0.058 (0.360)	-0.013 (0.843)	-0.078 (0.211)		
Less risk averse	-0.032 (0.703)	-0.039 (0.623)	-0.051 (0.514)	-0.033 (0.675)	-0.050 (0.517)		
Less disposition effect	**-0.169** **(0.011)**	**-0.172** **(0.007)**	**-0.180** **(0.005)**	**-0.176** **(0.006)**	**-0.191** **(0.003)**	**-0.174** **(0.006)**	**-2.315** **(0.001)**
Longer forecasting horizon	-0.164 (0.057)	-0.148 (0.075)	**-0.184** **(0.025)**	-0.149 (0.072)	**-0.184** **(0.025)**		
Less performance than others	-0.045 (0.630)						
Less information than others	0.046 (0.626)						
Less domestic information advantage	**-0.166** **(0.020)**	**-0.166** **(0.018)**	**-0.169** **(0.016)**	**-0.159** **(0.022)**	**-0.155** **(0.025)**	**-0.173** **(0.012)**	**-1.891** **(0.024)**
Higher Dax optimism	**0.047** **(0.021)**	**0.053** **(0.009)**	**0.052** **(0.010)**	**0.048** **(0.017)**	**0.048** **(0.018)**	**0.055** **(0.006)**	**0.562** **(0.018)**
Constant 1	-4.571	-4.511	-4.745	-4.259	-4.098	-4.146	
Constant 2	-1.046	-1.106	-1.385	-0.948	-0.826	-0.794	
Constant 3	0.051	-0.023	-0.323	0.113	0.219	0.289	**42.690** **(0.000)**
Constant 4	1.015	0.960	0.627	1.090	1.179	1.265	
Constant 5	1.693	1.629	1.264	1.756	1.830	1.929	
LRT (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	
Pseudo R^2	0.061	0.057	0.044	0.046	0.036	0.053	0.138

† The variable home bias is measured in categories, ranging from $0 \leq w \leq 10\%$ (coded as 1), $10 < w \leq 30\%$ (coded as 2), … , $70 < w \leq 90\%$ (coded as 5) to $90 < w \leq 100\%$ (coded as 6).
All p-values are based on a bootstrap with 250 replications for the respective specification. Bold numbers represent coefficient estimates that are significant at least on the level of five percent.
‡ This specification shows results from censored linear regressions (censoring at zero and 100) where the dependent variable is the percentage share of assets allocated to Germany. The last row gives the usual adj. R^2 and the usual intercept is reported in the "constants" row.

Table 5.5 Determinants of (less) reluctance to loss realization
All p-values are based on a bootstrap with 250 replications for the respective specification. Bold numbers represent coefficient estimates that are significant at least on the level of five percent.

Dependent variable: reluctance to loss realization (6 categories)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Institutional investors	**0.618** **(0.034)**	**0.611** **(0.021)**	**0.723** **(0.011)**			**0.616** **(0.010)**	**0.590** **(0.012)**
Investment advisors	-0.138 (0.612)	-0.152 (0.560)	-0.021 (0.929)				
More experienced	**0.167** **(0.012)**	**0.166** **(0.011)**		**0.181** **(0.006)**		**0.155** **(0.004)**	**0.175** **(0.001)**
Worse variance forecast	**-4.059** **(0.042)**	**-4.043** **(0.028)**			-4.030 (0.059)	**-4.657** **(0.023)**	**-4.607** **(0.011)**
Higher age	-0.038 (0.706)	-0.035 (0.764)	0.060 (0.563)	-0.078 (0.424)	0.020 (0.828)		
University degree	0.058 (0.771)	0.055 (0.776)					
More senior	0.278 (0.282)	0.275 (0.289)					
Higher share of equities	0.001 (0.577)	0.002 (0.590)	0.002 (0.538)	0.001 (0.623)	0.001 (0.654)		
More volume	-0.067 (0.270)	-0.070 (0.310)	-0.026 (0.705)	-0.061 (0.359)	-0.020 (0.763)		
Less risk averse	0.087 (0.298)	0.088 (0.275)	0.093 (0.196)	0.074 (0.325)	0.086 (0.267)		
Less disposition effect	**0.282** **(0.000)**	**0.276** **(0.000)**	**0.284** **(0.000)**	**0.273** **(0.000)**	**0.288** **(0.000)**	**0.234** **(0.000)**	
Longer forecasting horizon	**0.212** **(0.012)**	**0.214** **(0.008)**	**0.242** **(0.002)**	**0.219** **(0.004)**	**0.243** **(0.003)**	**0.201** **(0.010)**	**0.184** **(0.010)**
Less performance than others	0.037 (0.658)						
Less information than others	0.150 (0.089)	0.164 (0.064)	0.117 (0.172)	0.136 (0.088)	0.082 (0.362)	0.165 (0.057)	**0.168** **(0.023)**
Constant 1	-0.860	-0.960	-0.839	-0.922	-1.385	-1.354	-2.104
Constant 2	1.415	1.312	1.399	1.328	0.853	0.884	0.105
Constant 3	2.361	2.257	2.321	2.257	1.774	1.798	0.995
Constant 4	3.305	3.202	3.248	3.182	2.695	2.726	1.884
Constant 5	4.607	4.164	4.536	4.465	3.970	4.019	3.157
LRT (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.041	0.040	0.032	0.032	0.029	0.036	0.025

Appendix 1. Survey participants' objective attributes

		Responses (in percent)				
		all	Institutional investors	Investment advisors	Individual investors	KW Test
Age	<25 years	4.2	0.0	5.3	4.9	4.23 **(0.00)
	25-35	28.6	39.0	42.1	23.3	
	36-45	34.8	50.6	38.2	30.5	
	46-55	19.7	10.4	11.8	23.5	
	56-65	9.5	0.0	2.6	13.1	
	>65	3.2	0.0	0.0	4.7	
	mean	41.1	37.1	36.4	43.1	
	obs	497	75	78	344	
(Investment) Experience	<4 years	5.1	2.7	0.0	7.0	3.39 **(0.00)
	4-6	20.9	9.5	21.1	23.7	
	7-9	18.0	14.9	11.8	20.3	
	10-12	13.3	21.6	5.3	13.3	
	13-15	9.8	14.9	13.2	7.7	
	>15	32.9	36.5	48.7	28.0	
	mean	12.0	13.5	14.2	11.1	
	obs	497	75	78	344	
University degree (yes)		66.8	62.3	63.5	68.6	0.17 (0.87)
	obs	485	75	76	334	
Gender (Male)		0.98	0.96	0.98	0.96	0.11 (0.92)
	obs	497	75	78	344	
Hierarchy	Junior	16.8	17.6	25.0	13.3	2.83 **(0.01)
	Senior	43.1	52.7	54.7	34.3	
	Head of …	40.1	29.7	20.3	52.4	
	obs	477	74	74	329	
(Higher) Wealth in thousand EUR (Portfolio volume)	$0 \leq x \leq 10$	14.62	10.77	12.5	15.89	1.81 (0.07)
	$10 < x \leq 50$	33.87	33.85	31.25	34.44	
	$50 < x \leq 250$	33.41	24.62	45.31	32.78	
	$250 < x \leq 1{,}000$	10.44	6.15	7.81	11.92	
	$x > 1{,}000$	7.66	24.62	3.13	4.97	
	mean	241.2	455.4	173.7	209.3	
	obs	491	74	77	340	
Share of equities†	$0 \leq x \leq 20\%$	35.81	32.00	30.77	37.79	0.60 (0.55)
	$20 < x \leq 40\%$	19.52	25.33	16.67	18.90	
	$40 < x \leq 60\%$	16.30	16.00	19.23	15.70	
	$60 < x \leq 80\%$	14.89	10.67	20.51	14.53	
	$80 < x \leq 100\%$	13.48	16.00	12.82	13.08	
	mean	40.1	40.7	43.6	39.2	
	obs	497	75	78	344	

† Share of equities denotes the share of total investment volume that is invested in equities

Appendix 2. Responses in percent and descriptive statistics

Item		all	Institutional investors	Investment advisors	Individual investors	KW Test
1. Higher turnover	Mean	43.45	38.12	43.70	44.62	2.47
	Obs	457	74	73	310	(0.29)
2. More home bias	Mean	29.65	19.18	31.75	31.45	23.28
	obs	465	74	76	315	**(0.00)
3. Less reluctance to loss realization	Mean	3.97	4.34	3.77	3.94	6.05
	obs	455	74	73	308	*(0.05)
4. Worse variance forecast	Mean	6.09	6.16	6.00	6.10	0.28 (0.87)
	Median	5.23	4.83	5.35	5.36	
	Minimum	0.01	0.13	0.01	0.07	
	Maximum	30.15	26.65	28.06	30.15	
	obs	450	74	76	300	
5. Less risk averse	Very risk averse	0.65	0.00	1.32	0.63	0.52 (0.77)
	2	9.68	8.11	7.89	10.48	
	3	15.05	22.97	14.47	13.33	
	4	20.86	21.62	19.74	20.95	
	5	35.27	27.03	38.16	36.51	
	Little risk averse	18.49	20.27	18.42	18.10	
	obs	465	74	76	315	
6. Less disposition effect	Complete approval	6.85	1.37	6.49	8.13	0.91 (0.63)
	2	18.88	20.55	18.18	18.67	
	3	24.07	24.66	29.87	22.59	
	4	21.16	26.03	23.38	19.58	
	5	13.90	10.96	9.09	15.66	
	Complete disapproval	15.15	16.44	12.99	15.36	
	obs	482	73	77	332	
7. Longer forecasting horizon	Days	14.88	9.33	11.69	16.87	6.41 *(0.04)
	Weeks	22.73	18.67	15.58	25.30	
	2-6 months	31.20	37.33	36.36	28.61	
	6-12 months	18.60	22.67	20.78	17.17	
	Years	12.60	12.00	15.88	12.05	
	obs	484	75	77	332	
8. Less performance than others	Much better	12.63	13.33	19.48	10.91	27.67 **(0.00)
	2	15.07	28.00	22.08	10.62	
	3	25.25	28.00	29.87	23.60	
	4	35.64	25.33	24.68	40.41	
	5	5.91	2.67	2.60	7.37	
	6	3.05	1.33	0.00	4.13	
	Much worse	2.44	1.33	1.30	2.95	
	obs	491	75	77	339	
9. Less information than others	Much better	30.55	56.00	49.35	20.65	57.02 **(0.00)
	2	28.31	21.33	32.47	28.91	
	3	17.72	12.00	14.29	19.76	
	4	20.57	10.67	3.90	26.55	
	5	1.22	0.00	0.00	1.77	
	6	1.02	0.00	0.00	1.47	
	Much worse	0.61	0.00	0.00	0.88	
	obs	491	75	75	339	
10. Less domestic information advantage	Complete approval	2.70	2.78	3.90	2.40	6.33 *(0.04)
	2	16.80	22.22	20.78	14.71	
	3	26.76	20.83	35.06	26.13	
	4	18.46	25.00	11.69	18.62	
	5	20.95	15.28	19.48	22.52	
	Complete disapproval	14.32	13.89	9.09	15.62	
	obs	482	72	77	333	
11. Higher DAX optimism	Mean	-0.72	-0.25	-0.88	-0.79	1.16 (0.56)
	Standard deviation	4.83	4.50	4.50	4.99	
	Skewness	-0.68	-0.54	-1.06	-0.62	
	Kurtosis	5.53	3.37	6.52	5.63	
	obs	450	74	76	300	

Appendix 3. Marginal effects at variable medians

This table shows marginal effects for the ordered logit models documented in tables 5 and 6, respectively. Panel A shows marginal effects for the home bias regressions (table 5, specification 6), Panel B shows marginal effects for the turnover regressions (table 6, specification 6) and Panel C marginal effects for the reluctance to loss realization (table 7, specification6) . All marginal effects are evaluated at variable medians.

Panel A: Marginal effects for determinants of turnover

Variable	Pr(x≤10)	Pr(10<x≤25)	Pr(25<x≤50)	Pr(x>50)
Institutional investors	0.035	0.090	0.018	-0.144
More experienced	0.005	0.016	0.007	-0.028
Worse variance forecast	-0.002	-0.005	-0.002	0.009
Higher age	0.008	0.026	0.012	-0.046
Less risk averse	-0.019	-0.060	-0.028	0.108
Longer forecasting horizon	0.024	0.075	0.034	-0.133
Less performance than others	0.017	0.053	0.024	-0.094
unconditional probability	0.047	0.199	0.261	0.493

Panel B: Marginal effects for determinants of home bias

Variable	Pr(0≤w≤10)	Pr(10<w≤30)	Pr(30<w≤50)	Pr(50<w≤70)	Pr(70<w≤90)	Pr(w>90)
Institutional investors	0.077	0.135	-0.099	-0.062	-0.023	-0.028
More experienced	0.008	0.036	-0.016	-0.015	-0.006	-0.008
Worse variance forecast	-0.002	-0.009	0.004	0.004	0.002	0.002
Higher age	-0.011	-0.045	0.020	0.018	0.008	0.010
Less disposition effect	0.008	0.034	-0.015	-0.014	-0.006	-0.007
Less domestic information advantage	0.008	0.034	-0.015	-0.014	-0.006	-0.007
Higher Dax optimism	-0.003	-0.011	0.005	0.004	0.002	0.002
unconditional probability	0.048	0.543	0.219	0.109	0.038	0.043

Appendix 3. *(continued)*

Panel C: Marginal effects for determinants of reluctance to loss realization

Variable	Complete approval	2	3	4	5	Complete disapproval
Institutional Investors	-0.012	-0.070	-0.051	-0.018	0.058	0.094
More experienced	-0.004	-0.021	-0.012	0.000	0.017	0.019
Worse variance forecast	0.001	0.006	0.004	-0.000	-0.005	-0.006
Longer forecasting horizon	-0.005	-0.027	-0.015	0.000	0.023	0.025
Less disposition effect	-0.006	-0.032	-0.018	0.000	0.026	0.029
Less information than others	-0.004	-0.023	-0.012	0.000	0.019	0.020
unconditional probability	0.027	0.177	0.186	0.228	0.237	0.145

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