Heiko Jacobs

Empirical essays on the stock market impact of limited investor attention

Inauguraldissertation
zur Erlangung des akademischen Grades
eines Doktors der Wirtschaftswissenschaften
der Universität Mannheim

vorgelegt im Herbst-/Wintersemester 2011/2012

Dekan:	Dr. Jürgen M. Schneider
Referent:	Professor Dr. Dr. h.c. Martin Weber
Korreferent:	Professor Dr. Erik Theissen
Tag der mündlichen Prüfung:	28. November 2011

Meinen Eltern

Acknowledgements

This thesis is the result of a four year working period at the University of Mannheim. I have to thank many for their encouragement, inspiration, and support during this period.

I am deeply indebted to my supervisor Prof. Dr. Dr. h.c. Martin Weber. His professional and personal guidance through my time at his chair, his insights as well as his motivating support have been of great value to me. Without him, writing this thesis would have been much harder and, after all, less enjoyable.

I would also like to express my gratitude to Prof. Dr. Erik Theissen, my second examiner.

My former and current colleagues at the chair of business administration and finance, especially banking, have played a decisive role in revising and improving my research with numerous helpful comments and suggestions. I appreciate the collaboration with Dr. Sebastian Müller, who coauthored one study in this dissertation (chapter 5), Dr. Sina Borgsen, Christian Ehm, Dr. Daniel Foos, Prof. Dr. Markus Glaser, Justus Heuer, Christine Kaufmann, Christoph Merkle, Prof. Dr. Lars Norden, Dr. Alen Nosic, Dr. Philipp Schmitz, Philipp Schreiber, Ulrich Seubert, Daniel Smith, Dr. Sascha Steffen, and Dr. Frank Welfens. This thesis has further benefited from the excellent work of many former as well as current student assistants. Among them, I would like to particularly thank Andreas Dzemski, Alexander Hillert, and Erdal Talay.

For their valuable input, I am grateful to many unnamed referees, discussants as well as participants at about a dozen conferences and summer schools. Mark Seasholes, an anonymous referee, and Burton Hollifield (as editor of the Review of Finance) further provided many valuable suggestions that considerably improved chapter 2 of this thesis.

Most of all, I would like to thank my parents Monika and Bernd. Without their loving support and sincere encouragement throughout my whole life, this thesis would have never been possible.

Mannheim, November 2011

Contents

List of Figures

List of Tables

List of Symbols

$\widehat{\alpha}$	Estimated regression constant from the market model
α^{3F}	Regression constant from a three factor model
α^{4F}	Regression constant from a four factor model
α^{10F}	Regression constant from a ten factor model
$\widehat{\beta}$	Estimated regression coefficient from the market model
β	Regression coefficient (various models)
ε	Residual from a regression (various models)
μ	Vector of expected stock returns
σ	Standard deviation (various models)
σ_{bm}	Standard deviation of the benchmark return

$AR_{i,t}$	Return shock of market segment i on day t
c_t	Costs of rebalancing in period t
$Distraction_t$	Raw distraction measure for day t
$E[TO_{i,t}]$	Expected turnover of firm i on day t
$Hol_{i,t}$	Dummy variable that equals one if a firm's headquarter is located in a holiday region
$HML_{i,t}$	Return difference between stocks with high and low equity book-to-market ratios (in period t for market i)
MKT_t	Excess return of a global equity portfolio in period t
$News_{i,t}$	Dummy variable indicating whether there is published news for firm i in period t

R^2	Coefficient of determination from a regression model
$R_{m,t}$	Value-weighted market return on day t
$R_{i,t}$	Return of stock i on day t
$Ret_{+,i,t}$	Return of stock i on day t if positive and zero otherwise
$Ret_{-,i,t}$	Return of stock i on day t if negative and zero otherwise
$r_{bm,t}$	Benchmark return in period t
$r_{i,t}$	Return of strategy i in period t
$r_{f,t}$	Return of the risk-free asset in period t
$Ratio_{i,t}$	Fraction of "holiday firm trading" by online broker investors on day t divided by the fraction of "holiday firm trading" by the whole market on day t
$Return\,Gap_t$	Return gap in month t
s	Bid-ask spread
$SMB_{i,t}$	Return difference between small and large capitalization stocks (in period t for market i)
$TO_{i,t}$	Turnover of firm i on day t
$TO_{m,t}$	Value-weighted market turnover on day t
w	weight (various models)
$WML_{i,t}$	Return difference between stocks with high and low past stock returns in period t for market i

List of Abbreviations

AG	Aktiengesellschaft
AHGZ	Allgemeine Hotel- und Gastronomie-Zeitung
AMEX	American Stock Exchange
AR	Autoregressive
ASX	Australian Securities Exchange
BM ratio	Equity book-to-market ratio
BP	Basis points
CAPM	Capital asset pricing model
CBS	Central Bureau of Statistics
CRSP	Center for Research in Security Prices
DAX	Deutscher Aktienindex
ddp	Deutscher Depeschendienst
DGAP	Deutsche Gesellschaft fuer Adhoc-Publizität
DJNS	Dow Jones News Service
DLC	Dual-listed company
DPA	Deutsche Presseagentur
EU	European Union
ETF	Exchange traded funds
Euribor	Euro Interbank Offered Rate
Fibor	Frankfurt Interbank Offered Rate
FTD	Financial Times Deutschland
FTSE	Financial Times Stock Exchange
GDP	Gross domestic product
GICS	Global Industry Classification Standard
GSCI	Goldman Sachs Commodity Index
HD	High distraction

HEX	Helsinki Stock Exchange
HML	High minus low
I/B/E/S	Institutional Brokers' Estimate System
IMF	International Monetary Fund
IVW	Informationsgemeinschaft zur Feststellung der Verbreitung von Werbeträgern e.V.
LD	Low distraction
Mio.	Million
MSCI	Morgan Stanley Capital International
NASDAQ	National Association of Securities Dealers Automated Quotation
NBER	National Bureau of Economic Research
NYSE	New York Stock Exchange
N.V.	Naamloze vennootschap
OLS	Ordinary least squares
PLC	Public Limited Company
PPP	Purchasing power parity
RI	Total return index from Thomson Reuters Datastream
RMRF	Excess return of the German stock market
S&P	Standard & Poor's
SAVE	Sparen und Altersvorsorge in Deutschland
SBF	Société des Bourses Françaises
SD	Standard deviation
SIC	Standard Industrial Classification
SMB	Small minus big
TAQ	Trade and Quote
T-bills	Treasury bills
UK	United Kingdom
US	United States
USD	United States Dollar
VIX	Chicago Board Options Exchange Market Volatility Index
WML	Winners minus losers

Chapter 1

General Introduction

1.1 Motivation and Background

1.1.1 Overview

How markets impound information into asset prices is one of the major concerns of financial economics. Standard asset pricing models are typically built on the premise that new information is reflected immediately in equilibrium prices, which consequently provide the best possible estimate of fundamental asset values. Investors are effectively assumed to have infinite time and processing resources, which enable them to gather and process all value-relevant signals instantaneously and appropriately. These assumptions, however, stand in stark contrast to a large body of psychological research which has documented that humans find it hard to respond to multiple information signals or to perform several tasks simultaneously. Directing attention towards one stimulus necessarily goes along with a reduction of attention towards other tasks. In short, human attention is limited and must be selective.

Motivated by this long-standing and intuitively appealing evidence, a rapidly growing stream of theoretical and empirical research highlights the importance of attention constraints in finance. This work suggests that market participants' limited attention may be important not only for individual behavior, but also for equilibrium market outcomes. Yet despite the well-known relevance of attention constraints for human decision making, financial research has only recently addressed their potentially powerful role in a comprehensive and rigorous way. As a consequence, the impact of investor attention constraints on financial markets is still far from being well understood.[1]

Against this background, the major goal of this thesis is to broaden and deepen the understanding on how limited investor attention affects economic aggregates in financial markets. In doing so, this thesis aims to contribute to a fundamental debate in behavioral economics: Do phenomena in individual behavior matter in that they extend to the market level?

More specifically, this thesis consists of four distinct research projects. Each of the first three derives implications of limited investor attention for equilibrium outcomes at the stock-level, and then subsequently investigates their empirical validity in depth. In this way, the thesis uncovers and explains several novel patterns in turnover and return data. A fourth empirical study explores the relative performance of simple portfolio diversification strategies, whose design might be considered as meeting the needs of cognitively overloaded private investors.

1.1.2 Attention Constraints and Individual Decision Making in Financial Markets

Laboratory studies in psychology have accumulated comprehensive evidence that attention is a limited resource (Kahneman (1973)). Subjects can focus their attention on a particular stimulus only at the expense of other stimuli in the environment.[2] As for instance a literature survey by Pashler (1998) reveals, it has been known for a long time that performance typically suffers if individuals aim at carrying out several mental tasks at the same time.

[1] This view is also expressed in a number of recent quotes. For example Camerer (2006) notes: "Attention is perhaps the ultimate scarce cognitive resource. A few studies have started to explore its implications for economics." (p.202). Cohen and Frazzini (2008) state that "there is a large body of literature in psychology regarding individuals' ability to allocate attention between tasks". (...) "An empirical literature is also beginning to build regarding investor limited attention." (p.1981). Corwin and Coughenour (2008) point out that "despite the documented importance of limited attention in other settings, its impact on financial markets has only recently attracted attention." (p. 3064).

[2] An often cited example in this context are dichotic listening tasks (Broadbent (1953)). In its simplest form, subjects are exposed to two different auditory stimuli simultaneously, one played to each ear. They are instructed to extract the information contained in one of the stimuli. When afterwards asked about the second stimulus, subjects can typically remember very little.

Yet despite the intuitive appeal of these findings, the question to what extent they matter for the quality of decision making in financial markets has only recently become the subject of intensive investigations. This may seem surprising as asset markets provide a natural setting for exploring consequences of decision markers' time and processing constraints. Market participants are constantly faced with an abundance of information signals, which moreover widely vary in strength and precision. However, time and attention are costly. Consequently, market participants have to be very careful and selective in distilling and processing this vast amount of information in a short period of time. Optimally allocating finite resources in this context is a complex and demanding task. It therefore seems reasonable to hypothesize that attention constraints may potentially have far-reaching implications for many aspects of financial markets.

However, a key obstacle to work aiming at empirically investigating this conjecture is that investor attention allocation is typically not observable. As Barber and Odean (2008) put it: "A direct measure would be to go back in time and, each day, question (...) investors (...) as to which stocks they thought about that day." (p.787). In contrast to laboratory experiments in psychological research, attention in real financial markets can hardly be measured directly. A challenge for empirical work is therefore to design promising indirect measures for attention allocation. An emerging stream of literature addresses this issue by developing and testing conceptually quite diverse proxies for limited investor attention, both in the time-series and in the cross-section.[3] Chapter 3 and chapter 4 of this thesis aim at progressing on this front.

Which market participants are likely to be affected by attention constraints? It is natural to assume that information processing constraints should be particularly binding for retail investors. And indeed, the empirical literature on the trading behavior of individual investors supports this conjecture. Findings thereby also typically suggest that the attention-driven nature of retail investors' behavior negatively affects their performance.[4] For example, the common theme underlying the studies of Barber and Odean

[3] The time-series perspective is taken by e.g. Bagnoli et al. (2006), DellaVigna and Pollet (2009), Hirshleifer et al. (2009), Hou et al. (2009), Peng et al. (2007), and Peress (2008). The cross-sectional view is considered in e.g. Barber and Odean (2008), Da et al. (2011), Grullon et al. (2004), Engelberg (2008), Hou et al. (2009), Lou (2010), and Loh (2010).

[4] Work in other areas of economics strengthens the conjecture that limited attention might adversely effect individuals' welfare. For instance, see Hossain and Morgan (2006) for inattention towards shipping costs in eBay auctions or Chetty et al. (2009) for inattention to intransparent taxes. See DellaVigna (2009) for a recent overview.

(2008), Engelberg et al. (2011), Lou (2010), and Seasholes and Wu (2007) is to reveal that retail investors are net buyers of attention-grabbing stocks, which subsequently underperform. This finding is in line with an extant literature which documents that retail investors are particularly susceptible to a number of costly decision-making mistakes.[5] In fact, "these discrepancies, or investment mistakes, are central to the field of household finance." (Campbell (2006), p. 1554.) Against this background, chapter 5 of this thesis is devoted to evaluate easy to implement asset allocation strategies as a possible remedy against this widespread behavior of cognitively overloaded private investors.[6]

However, the impact of limited attention does not seem to be restricted to this specific subgroup of market participants. For instance, Kacperczyk et al. (2011) provide evidence suggestive of mutual fund managers exhibiting limited attention. References in Hirshleifer and Teoh (2003) suggest that analysts fail to take value-relevant financial statement information into account. Corwin and Coughenour (2008) show that time and processing constraints negatively affect the liquidity provision of market makers, in particular in busy moments. Limited attention is rooted in human cognitive resource constraints. In varying degrees, it therefore matters for all market participants, including sophisticated financial professionals (e.g. Libby et al. (2002), Hirshleifer et al. (2004), Hirshleifer et al. (2009), Huang and Liu (2007)).

1.1.3 Attention Constraints and Stock Market Outcomes

Limited attention might matter at the individual level, but does it also matter for economic aggregates? There is clearly a strong demand to evaluate whether limited attention is merely an interesting aspect of market participants' behavior, or whether it has important implications for equilibrium outcomes. But in which ways might attention-driven

[5] See e.g. Barber and Odean (2011) for a recent review. Among the best documented investment mistakes are the following: Retail investors show a disposition to sell winning stocks too early and hold on to losing stocks too long (e.g. Odean (1998), Shefrin and Statman (1985), and Weber and Camerer (1998)). They often trade excessively (e.g. Barber and Odean (2000), and Odean (1999)). They tend to forgo the benefits of diversification (e.g. Benartzi (2001), French and Poterba (1991), Goetzmann and Kumar (2008), Grinblatt and Keloharju (2001), Kilka and Weber (2000)).

[6] It should be noted that limited attention per se is not a behavioral bias, as it merely reflects constraints in human information processing (e.g Hou et al. (2009)). However, it is likely to be related to or to interact with well-known biases. For example, Yuan (2009) finds that attention-constrained retail investors suffer from more pronounced disposition effects. Hirshleifer and Teoh (2003) conjectures that narrow framing (Kahneman (2003)), i.e. the tendency to buy and sell assets without considering total portfolio effects, is rooted in information processing constraints.

individual decisions affect market behavior? The literature so far has proposed a number of answers, which also depend on which specific variables and settings one is interested in. The empirical studies in this thesis shed further light on the role of limited attention for stock-level turnover (chapter 2) as well as for the price discovery of economically linked stocks (chapter 3 and 4).

The impact limited investor attention can have on aggregate stock-level trading volume is, to some extent, obvious: In their investment decision, investors can only consider stocks whose existence they are aware of (e.g. Merton (1987)). Consequently, attention towards a certain firm is simply a necessary condition for trading its stock (e.g. Hou et al. (2009)). Apart from this very basic relationship, several theories and empirical findings suggest more specific mechanisms for how the link between attention and trading volume might work. For instance, if (at least some) attention-constraint investors form their expectations on the basis of only a subset of publicly available information (e.g. Hong and Stein (1999)), differences of opinion might become more pronounced. To the extent that investors do not sufficiently adjust for the fact that they are not basing their valuations on all relevant information, trading volume might increase (e.g. Hong and Stein (2007)). This effect might be even more pronounced if attention constraints and behavioral biases such as overconfidence or self-attribution bias are present simultaneously (e.g. Hou et al. (2009), Daniel et al. (1998)). Investors then might pay selective attention towards news that confirms their private information, whose precision might consequently be overestimated.

A different line of arguments suggests that cognitively overloaded investors might have preferred habitats, i.e. choose to trade only a specific subset of available securities, to reduce the complexity of investment decisions (e.g. Barberis and Shleifer (2003), Barberis et al. (2005)). If a stock belongs to the habitat of particularly many investors, it is more likely to be traded than the stocks of otherwise comparable firms (e.g. Loughran and Schultz (2005)). In a similar vein, attention-grabbing stocks might ceteris paribus be more likely to be heavily traded, as these stocks solve the search problem of which stock to invest in. When there are many alternatives such as the thousands of stocks available in financial markets, options that particular catch attention are natural candidates. In line with this reasoning, Barber and Odean (2008), Engelberg et al. (2011), among others, show that retail investors excessively invest in attention-grabbing stocks. Moreover, there is convincing evidence that stale news, which however is broadcasted in an attention-grabbing matter, leads to increased trading (e.g. Huberman (2001), Gilbert et al. (2011), Tetlock (2011)). Finally, Grullon et al. (2004) and Chemmanur and Yan (2009) show that the stocks of firms with high advertising expenditures are, ceteris paribus, more heavily traded.

Approaches proposing that investor attention constraints also matter for price discovery in financial markets arguably often face higher hurdles. A key obstacle to any attention-based theory of mispricings is that it first has to convincingly argue why arbitrageurs should fail to keep asset prices close to the fundamental values implied by standard models. In efficient markets in the sense of Fama (1970), arbitrage is the crucial force which ensures that actual stock prices equal the fundamental value of the firm. In this classical view, as soon as the actions of less than fully rational investors cause stock prices to deviate from their true value, rational arbitrageurs will step in. They will aggressively bet against the mispricings, thereby bringing prices back in line with their fundamentally justified level. According to this textbook view, arbitrageurs will implement zero-cost trading strategies to gain close to riskless profits at the expense of less rational traders.

This traditional view, however, has been challenged by a strand of research, which is commonly referred to as the "limits to arbitrage" literature. In essence, this work argues that strategies designed to correct deviations from fundamental values can, in reality, be both risky and costly. Moreover, arbitrageur capital might be subject to financial constraints, induced by e.g. agency conflicts. As a consequence, arbitrageurs might have less incentives or less possibilities to quickly eliminate even apparent mispricings, which therefore might persist at potentially substantial levels and for potentially long periods of time. By now, both the theoretical and empirical literature on impediments to arbitrage is comprehensive[7], and a broad consensus with regard to the key frictions and major forces has emerged. Barberis and Shleifer (2003) refer to the insights obtained from this work as "one of the biggest successes of behavioral finance" (p. 1053). Investor psychology and limits to arbitrage are often considered the two building blocks of behavioral finance needed to explain return anomalies, which are difficult to reconcile with standard asset pricing models (e.g. Shleifer and Summers (1990), Gromb and Vayanos (2010)).

[7] A small selection includes Abreu and Brunnermeier (2002), Jong et al. (2009), Long et al. (1990), Hong et al. (2011), Pontiff (2006), Shleifer and Vishny (1997), and Shleifer (2000). See Gromb and Vayanos (2010) for a recent review of the literature.

In the light of such limits to arbitrage, attention-driven investment behavior is likely to leave discernible traces in stock return data. Recent studies provide theoretical frameworks in which investor attention constraints can affect asset pricing statics and dynamics. Moreover, a growing empirical work tests implications derived from these models. For instance, informationally overloaded investors may be slow in incorporating publicly available information immediately into prices.[8] This gradual information flow will lead to stock price underreaction, giving rise to return predictability.[9] Information will not be completely incorporated into asset prices until investors fully pay attention to it.

The prominence with which (actual or stale) news is revealed appears crucial in this context (e.g. Hong and Stein (2007)). A substream of the literature proposes that attention-driven noise traders may excessively focus on attention-grabbing stocks, thereby inducing price pressure and stock price overreaction.[10] In this sense, investor attention constraints appear to play a dual role (e.g. Hou et al. (2009)).

Finally, limited investor attention may also cause more subtle patterns in price discovery. For example, cognitively overloaded investors might have a tendency to categorize stocks into broad classes, such as local or value stocks, instead of focussing on individual firms. Processing information and making investment decisions primarily at the aggregate category level might subsequently induce excessive comovements of stock returns, as firms in the respective class are treated (too) equally.[11]

---

[8] A vivid and clean example is given in Huberman and Regev (2001). The authors run a case study on the price discovery of a single biotech company named EntreMed. Huberman and Regev (2001) document that its stock price more than tripled in May 1998 as a consequence of seemingly breaking news made public on a front-page article in the New York Times. Remarkably, however, this article was in fact based on stale news. The substance of the story had already been released months earlier - in a less attention-grabbing manner in the less widely read scientific magazine “Nature”.

[9] Papers representing this line of reasoning include Cohen and Frazzini (2008), DellaVigna and Pollet (2007), DellaVigna and Pollet (2009), Hirshleifer and Teoh (2003), Hirshleifer et al. (2009), Hong and Stein (1999), Hong et al. (2007), Hou and Moskowitz (2005), Menzly and Ozbas (2010), and Peress (2008).

[10] Papers representing this line of reasoning include e.g. Barber and Odean (2008),Engelberg et al. (2011), and Seasholes and Wu (2007).

[11] Theoretical work includes e.g. Barberis and Shleifer (2003), Peng (2005), or Peng and Xiong (2006). Empirical work has addressed a number of different settings. For instance, see Cooper et al. (2001) and Cooper et al. (2005) on the effect of name changes, Barberis et al. (2005), Greenwood (2008), or Boyer (2011) on index effects, Green and Hwang (2009) on price effects, or Pirinsky and Wang (2006) on location effects.

1.2 Outline of the Thesis and Main Results

This thesis is a collection of four empirical research projects which are devoted to several of the above raised issues. The remainder of the this section will shortly summarize the chapters and their main results in turn.

In chapter 2 (joint with Martin Weber), we exploit exogenous variation in limited investor attention along a geographical line in order to analyze whether localized trading is an important driver of firm-level turnover.

Specifically, based on the well-documented fact that investors have a strong preference for trading stocks of locally headquartered firms, we investigate the following research questions: Is individual local bias strong and pervasive enough to materially affect the cross-section of stock turnover at the firm level? If so, which firms and which investor groups tend to be most affected? Are there cross-sectional regularities in stock-level trading volume related to firm location, firm visibility, and investor clienteles?

We shed light on these issues by running a series of natural experiments in the German stock market. Germany has several holidays which are legally observed only in some of its 16 states. These holidays are characterized by a limit or ban on work and official business (but not exchanges). Previous research and casual evidence suggest that both private and professional investors in holiday regions tend to be temporarily distracted and thus to often refrain from actively participating in the stock market on such days. A large and geographically concentrated subset of holiday-distracted investors would not have implications for the cross-section of stock turnover, if these investors traded the market portfolio. However, the combination of limited attention and local bias gives rise to a hypothesis untested so far: Stocks of firms located in holiday regions should ceteris paribus exhibit a more pronounced drop in turnover than stocks of firms located in unaffected regions. An advantage of the German setting is that both samples are similar and thus satisfy the requirements of a natural experiment: They are broadly homogenous with respect to e.g. the number of firms, industry composition, typical firm size, average stock risk-return profiles or (unconditional) turnover properties. Similar findings apply to important characteristics of individual investors.

We find strong support for our conjecture in the data. Stocks of firms located in holiday regions are (only) temporarily strikingly less traded, both in statistical and economic terms, than otherwise similar stocks of firms in non-holiday regions. The pure regional holiday-induced abnormal drop in turnover roughly ranges from 10% to 20%, and survives a number of sensitivity checks. We devote considerable effort to the question whether our findings are driven by a temporary change in the cross-section of information release. From a firm perspective, we analyze shocks in the release of corporate news. From a market perspective, we study shocks in the idiosyncratic component of stock returns. From an investors viewpoint, we explore shocks in the search frequency for firm names in Google. From an analyst perspective, we study shocks in the cross-section of stock recommendations. From a media point of view, we analyze shocks in press coverage. These tests only sporadically point to differences in information intensity.

We thus argue that our findings, in their entirety and robustness, are most plausibly explained with locally biased investors staying out of the market due to regional holidays. Consistent with this interpretation, the volume shock is particularly pronounced in stocks, which are small, hard to value or neglected by the press, and thus less visible to non-local investors. Trading records of about 3,000 German online broker investors provide additional supportive evidence. Private investors appear to drive the negative volume shock in small firms, in which their localized trading is concentrated.

While chapter 2 has focused on stock-level trading volume, chapter 3 (joint with Martin Weber) concentrates on stock-level price discovery. It does so by testing asset pricing implications of the investor attention shift hypothesis proposed in recent theoretical work (e.g. Peng and Xiong (2006)). Our objective here is to directly assess how the dynamics of investor inattention affect the relative pricing efficiency of linked assets. We thereby study a promising and so far widely neglected setting, which differs conceptually from the ones the literature on limited attention has addressed so far: Stock pairs trading (Gatev et al. (2006)), a popular proprietary relative arbitrage approach, which bets on the future performance of stocks with very similar past performance. More specifically, the major research questions dealt with are the following: How to proxy for unobservable investor attention allocation? Is the price formation of linked stocks affected by time-varying investor attention? More specifically, do shocks in limited attention towards firm-level information hinder market participants from keeping relative prices of stock pairs in line, thereby giving rise to cross-return predictability?

To answer these questions, we design a novel proxy for limited investor attention in the time series, which relies on the intuition behind recent models on the dynamics of attention allocation. It aims at identifying days on which market participants are likely to be forced to spend more (or less) resources than usual on understanding “the big picture”. The goal is to separate “high distraction days”, during which turbulent market conditions are assumed to demand investors full attention, from “low distraction days”, during which we expect sufficient resources to process complex interactions at the firm-level. We then test whether the proxy is able to to explain variations in the magnitude of profits to pairs trading, building on the idea that investors might “lose sight of the trees (stock-level information) for the forest (more aggregate information)”.

The nature of pairs trading is very simple. It consists of a formation period followed immediately by a trading period. In the first step, one identifies those stock pairs whose historical prices have moved together the most. In our analysis, we consider in total close to half a billion of eligible stock pairs. In the immediately following second step, one shorts the relatively overpriced winner and buys the relatively underpriced loser, whenever the cumulative returns have sufficiently diverged. If the future resembles the past, prices are likely to finally convergence again, thereby generating positive returns on zero-cost portfolios. Our baseline analysis here relies on findings from more than 300,000 round-trip trades. We are particularly interested in whether it makes any difference whether stocks diverge on high or low distraction days.

And indeed, we find broad, robust, and economically meaningful evidence for investor distraction effects. For instance, the average one-month return on those long-short US stock pairs in 1962 to 2008 which happen to open on high distraction days is about twice as high as the return on pairs which open on low distraction days. In line with the implications of limited investor attention, pairs diverging on high distraction days are far more likely to converge again within in the next few days. This finding is not limited to the US market. The return difference between high and low distraction days is a persistent phenomenon which, with varying degree, is observable in each of the eight major non-US stock markets we additionally study.

Alternative proxies for limited attention, which we derive from the previous literature, often have an incremental effect. US pairs opening immediately before holidays, when investor distraction is likely to be particularly high, tend to be more profitable and to converge more often than pairs on average. In line with our hypotheses, the impact of investor distraction appears lower for pairs consisting of firms from the same industry or for pairs consisting of whole value-weighted industries. Finally, pairs particularly neglected (covered) by the media appear more (less) profitable, and exhibit a higher (lower) sensitivity to changes in the level of investor distraction. Collectively, our results lend support to the notion that the relative efficiency of linked assets might not be stable over time, but be affected by short-term investor attention shifts.

Chapter 4 provides a natural extension of the line of arguments developed in the previous chapter. Again, it is concerned with the question whether attention shifts matter for price discovery of linked stocks. However, we now concentrate on twin stocks, i.e. on firms with a fundamental, contractual, and sometimes long-standing economic relationship. These firms have contractually agreed on pooling all their current and future operations and cash-flows, but remain separate entities with their own stock exchange listings in their own countries. Their typically large and liquid stocks can be considered close to perfect substitutes. No model of intrinsic value is required, which overcomes the bad model problem inherent in many asset pricing tests. These stocks should move in lockstep in frictionless, efficient markets.

However, their returns and prices often exhibit large deviations from theoretical parity. This puzzling finding has motivated substantial research and is by now widely considered a textbook example of apparent mispricings in financial markets (e.g. Barberis and Shleifer (2003)). Previous work has convincingly shown that arbitrage is limited, which can explains why mispricings might persist - but not why they arise in the first place. Why do investors at least temporarily fail to take the blatant fundamental relationship between twin stocks into account? What exactly causes returns of twin stocks to diverge?

Very little is known about the underlying mechanisms. We address this gap in the literature by exploring the role of time-varying investor attention as one potential source of temporary return deviations. The design of the baseline distraction proxy thereby closely follows the approach developed in chapter 3, so that the results might be considered as reconfirming its explanatory power.

Our main contribution is to show that changes in the level of daily and weekly return discrepancies of internationally listed twin stocks are indeed positively correlated with a number of conceptually quite diverse proxies deemed to measure changes in investor attention. These findings largely carry over to the price perspective. Price deviations from theoretical parity tend to be somewhat higher (lower) than usual in moments of high (low) investor distraction. In a related out of sample setting, we finally find supportive evidence from US dual-class shares.

Chapter 5 (joint with Sebastian Müller and Martin Weber) differs from the other research projects in that it does not focus on market-level implications of investor attention constraints. Instead, it is devoted to the evaluation of easily implementable asset allocation guidelines for individual investors. Such an analysis is important as the empirical literature has uncovered many costly investment mistakes of retail investors, out of which at least some appear to be linked to cognitive resource constraints. As a consequence, deriving feasible buy-and-hold diversification strategies might be considered a possible remedy against such investment biases.

Specifically, the project addresses the following research questions: From the perspective of retail investors in real-life situations, what is the most promising way to diversify? Do simple rules of thumb add value? To what extent do such heuristics underperform when benchmarked against sophisticated optimization models?

Our approach allows us to provide suggestions for the construction of a "world market portfolio" that is as ex-ante efficient as possible. Our contribution to literature is twofold. First, we compare a broad spectrum of heuristic portfolio policies with eleven promising model extensions of the Markowitz (1952) mean-variance framework. Second, we explicitly differentiate between two ways of diversification that are usually analyzed separately: International diversification in the stock market and diversification across different asset classes. Given our focus, we pay particular attention to the practicability of our results.

We find that none of the Markowitz-based portfolio models is able to significantly outperform simple heuristics out-of-sample. Our results reveal that in fact a very broad range of fixed-weight allocation policies offers similar diversification gains as even sophisticated and recently developed portfolio optimization approaches. This holds true for both international diversification in the stock market and diversification over different asset classes. We thus suggest a simple and cost-efficient allocation approach for private investors.

Chapter 2

The Trading Volume Impact of Local Bias: Evidence from a Natural Experiment*

2.1 Introduction

By now there is ample evidence that both private and professional investors have a strong preference for trading stocks of locally-headquartered firms. But is this so-called local bias strong and pervasive enough to matter for the cross-section of stock turnover at the firm level? To answer this question, we run a natural experiment in the German stock market.

Germany has several holidays which are observed only in some of its 16 states. While these holidays have a religious origin, they materially influence public life as a whole. Authorized by law, they are characterized by a limit or ban on work and official business (but not exchanges). Previous research (e.g. DellaVigna and Pollet (2009), Hong and Yu (2009), and Frieder and Subrahmanyam (2004)) and casual evidence suggest that both private and professional investors in holiday regions tend to be temporarily distracted and thus to often refrain from actively participating in the stock market on such days.

This exogenous variation in investor attention along a geographical line would not have implications for the cross-section of abnormal firm-level trading activity if investors traded

*This chapter is forthcoming in the Review of Finance.

the market portfolio. Only the aggregate level of trading volume might then be affected (e.g. Lo and Wang (2000)). However, the introduction of local bias gives rise to a cross-sectional hypothesis untested so far: Stocks of firms located in holiday regions (in the following referred to as holiday firms) should, all else equal, exhibit a more pronounced negative shock in trading activity than stocks of firms located in unaffected regions (in the following referred to as non-holiday firms). An advantage of the German setting is that both samples are similar and thus satisfy the requirements of a natural experiment: They are broadly homogenous with respect to e.g. the number of firms, industry composition, typical firm size, average stock risk-return profiles or (unconditional) turnover properties. Similar findings apply to important characteristics of individual investors.

Consistent with our line of reasoning, we indeed find that holiday firms are (only) temporarily strikingly less traded, both in statistical and economic terms. The negative shock in turnover relative to non-holiday firms ranges roughly from 10% to 20%. It is not affected by the inclusion of various control variables or several changes in methodology.

To the extent that news arrival triggers abnormal trading, one might be concerned that our findings could be driven by a temporary change in the cross-section of information release. Note, however, that the vast amount of firm-relevant news on a market, industry, style or other aggregated levels should not be affected by regional holidays. It is arguably only the structure of idiosyncratic firm-specific news, generated in or near a firm's headquarter, which might potentially be affected. Digging deeper, we explore this news-based explanation of our findings from five perspectives. From a firm perspective, we analyze shocks in the release of corporate news. From a market perspective, we study shocks in the idiosyncratic component of stock returns. From an investor's viewpoint, we explore shocks in the search frequency for firm names in Google. From an analyst perspective, we study shocks in the cross-section of stock recommendations. From a media point of view, we analyze shocks in press coverage. Overall, these tests (only) sporadically point to significant differences in information release. Thus, we cannot rule out the possibility of lower information intensity for holiday firms contributing to our results. However, we believe it is justified to argue that information effects are unlikely to fully explain the magnitude and robustness of the findings we document.

In line with a local bias explanation and the investor recognition hypothesis of Merton

(1987), the regional holiday effect is particularly pronounced for firms less visible to non-local investors. Market capitalization, idiosyncratic risk and residual media coverage are used as proxies for visibility. Finally, we study daily trading patterns of about 3,000 private investors from a German online broker. Consistent with implications of previous research, individual investors seem to disproportionately cause the negative turnover shock in smaller firms, in which their localized trading is concentrated.

Our study contributes to the literature in several ways. First, while prior research shows that investors are biased towards the stocks of nearby firms, we identify scenarios in which these individual preferences are strong and pervasive enough to materially affect the cross-section of stock turnover. To our knowledge, our novel approach thereby provides the first non-US evidence of local bias affecting market outcomes.

Second, our findings help to better understand determinants of stock-level trading volume, which plays an essential role in much research on liquidity, return predictability, behavioral finance or information asymmetries. For example, Hong and Stein (2007) note that "many of most interesting patterns in prices and returns are tightly linked to movements in volume" (p. 111). At the same time, empirical evidence on the drivers of its substantial variation both in the cross-section and time-series is scarce (see e.g. the discussions in Gao and Lin (2010), Statman et al. (2006) or Chordia et al. (2007)). We add to this literature by uncovering cross-sectional regularities related to firm location, firm visibility, and investor clienteles.

Third, a growing body of research builds on the idea of limited attention, whereby investors process only a subset of publicly available information due to attention capacity constraints. A challenge for empirical work is the identification of a suitable proxy for investor distraction. For example, Hou et al. (2009) rely on down market periods, while Hirshleifer et al. (2009) employ the number of competing earnings announcements. In a scenario related to ours, DellaVigna and Pollet (2009) analyze the market response to earnings announcements on Fridays, when, as they argue, investor inattention is more likely. Our findings highlight the role of regional holidays as a promising proxy for limited attention. We identify scenarios which seem to cause distraction of an important subset of investors, leading to market frictions in trading activity along a geographical line. Moreover, we explore which firms and investor groups tend to be most affected.

The remainder of this chapter is organized as follows. Section 2.2 discusses related research and develops our hypotheses. Section 2.3 describes sample characteristics. Section 2.4 contains the event study and explores alternative interpretations of our findings. Section 2.5 analyzes determinants of the regional holiday effect. Section 2.6 concludes.

2.2 Related Literature and Hypotheses

By now, there is extensive and robust evidence for local bias on an individual level.[1] However, research exploring its implications for return and volume patterns is still at the beginning and moreover limited to the US market. Pirinsky and Wang (2006) document an excessive comovement of local stock returns, which they attribute to correlated trading of local residents. Building on investors' consumption smoothing motives, Korniotis and Kumar (2010) argue that stock returns contain a predictable local component. The findings of Hong et al. (2008) suggest that, in the presence of only few local firms competing for investors' money, share prices of spatially close firms are driven up by the excess demand of proximate residents. In a current study based on intra-day data, Shive (2011) exploits large power outages to study the effect of local investor clienteles on pricing efficiency. Her study provides evidence that informed local investors play an important role in information processing and price discovery.

To the best of our knowledge, only two papers focus on the impact of local bias on firm-level turnover. Loughran and Schultz (2004) show, among other pieces of evidence, that the time zone in which a firm is headquartered triggers intraday trading patterns in its stock. Loughran and Schultz (2005) demonstrate that rural stocks are less liquid than urban stocks, which they attribute to the latter being local and thus visible to more potential

[1] Heterogeneous findings suggest that both informational and behavioral factors are likely to drive local bias. Studies attributing this behavior to a preference for investing into the familiar, to the pronounced visibility of local stocks or to incorrectly perceived information advantages include e.g. Bailey et al. (2008), Grinblatt and Keloharju (2001), Huberman (2001), Seasholes and Zhu (2010), and Zhu (2003). Papers arguing in favor of superior locally generated information include e.g. Baik et al. (2010), Bodnaruk (2009), Coval and Moskowitz (1999), Coval and Moskowitz (2001), Feng and Seasholes (2004), Ivkovic and Weisbenner (2005), and Massa and Simonov (2006). Moreover, recent studies of Brown et al. (2008), Hong et al. (2004), Hong et al. (2005), Ivkovic and Weisbenner (2007), and Shive (2010) show that local social interaction and neighborhood word-of-mouth effects strongly affect investment decisions. Local bias has been shown to be robust across countries, investor subgroups and sample periods. For the German market, combined findings from e.g. Dorn and Huberman (2005), Dorn et al. (2008), Hau (2001), and this study suggest that, in the overall picture, German investors pose no exception.

investors. They conclude that "much remains to be done on geography and asset pricing" (p. 363). We aim at taking a step in this direction by exploiting holidays which are observed only in some areas of Germany. In our baseline analysis, we focus on All Saints' Day as well as on Epiphany. All Saints' Day, celebrated on November 1, is legally recognized only in the states of Baden-Württemberg, Bavaria, Northrhine-Westphalia, Rhineland Palatinate, and Saarland. Epiphany, celebrated on January 6, is a legally recognized holiday only in the states of Baden-Württemberg, Bavaria, and Saxony-Anhalt. There are more regional celebrations in Germany (see the appendix). We partly rely on these holidays in later tests. However, focusing on Epiphany and All Saints' Day yields the most attractive event study properties: It is a yearly event which splits the market in two large disjunct groups with similar characteristics (see section 2.3 for details).

How holidays in general affect (in particular private) investors' trading behavior is an empirical question. On the one hand, one might expect increased trading activity, as investors may have more time to engage in the stock market. On the other hand, one might expect decreased trading activity, as investors could indulge in vacation activities and thus refrain from participation in the market. Indeed, previous work supports this second line of reasoning. Frieder and Subrahmanyam (2004) show that turnover drops during nationwide holidays. Hong and Yu (2009) provide evidence of aggregate trading activity in international stock markets (including Germany) being lower during summer holiday periods, which they dub a "gone fishin' effect". This seasonality in turnover seems to be caused by both private and professional investors. DellaVigna and Pollet (2009) report that trading activity immediately after earnings announcements made on Fridays is comparatively low, as investors tend to be absent-minded due to the upcoming weekend. With regard to the German setting, the idea of investors being temporarily distracted is backed up by anecdotal evidence from leading papers and news services.[2] Combined with local bias, this type of limited investor attention makes novel predictions. Specifically,

[2]For instance, *Die Welt* (May 27, 2005), *Financial Times Deutschland* (June 12, 2009), *Tagesspiegel* (June 12, 2009), *Stuttgarter Zeitung* (May 8, 2007; May 24, 2008), *DPA* (May 25, 2001), and *Dow Jones* (June 1, 2007) all report that many investors, both private and professional, stay out of the market on regional holidays and corresponding bridge days. Other articles indirectly point to (primarily retail) investor distraction. For example, *Frankfurter Rundschau* (October 30, 2004) and *Die Welt* (November 2, 2004) report that non-holiday states profit from increased holiday tourism. *AHGZ* (May 12, 2007), a magazine for the hotel and catering sector, states that retail sales volume is higher around regional holidays. *Spiegel Online* (June 14, 2006) and *ddp* (June 8, 2009) point to the danger of traffic jams due to the large number of people on a short holiday. *Sueddeutsche Zeitung* (October 31, 2000) writes about massive obstructions of traffic near graveyards on All Saints' Day, on which it is custom to honor the deceased.

if investors tend to heavily overweight local stocks in their investment decisions, then a large, geographically concentrated subset of holiday-distracted investors might temporarily change the cross-section of stock turnover:

Hypothesis 1: Due to local bias, trading activity during regional holidays will be significantly lower for firms in holiday regions.

This hypothesis is consistent with the trading volume implications of the habitat-based model of comovement in Barberis et al. (2005). Similarly, in the model of Merton (1987), investors are aware only of a subset of the stock universe. Consequently, the demand for each stock depends on its shadow cost of information. In equilibrium, firms recognized by less investors, will, all else equal, have fewer shareholders taking relatively large positions. It seems plausible to assume that investor recognition of a firm is negatively correlated with geographical distance. We thus expect the impact of local investors to be particularly strong for firms which are hardly visible to remote investors:

Hypothesis 2: The negative turnover shock will be more pronounced for those local firms which are less recognized by non-local investors.

We also explore whether there are differences across investor types, which empirical findings assess to be likely. The aforementioned evidence of limited stock market participation during holidays appears to hold particularly true for private investors. At the same time, retail stock ownership tends to be more exposed to local bias than institutional stock holdings (e.g. Grinblatt and Keloharju (2001)). Small firms have been shown to be investment habitats of retail investors (e.g. Dorn et al. (2008), Kumar and Lee (2006)), whose local bias is particularly concentrated in these stocks (e.g. Zhu (2003)). Thus, traces of retail investor behavior in firm-level turnover should be most easily detected in small stocks. Combined with the observation of Goetzmann and Kumar (2008) that those investors who trade excessively are particularly locally biased, the rich set of findings suggests:

Hypothesis 3: The negative turnover shock in smaller firms will be disproportionately caused by individual investors.

2.3 Sample Characteristics

We follow the consensus in the literature on local bias and use a firm's headquarter as a proxy for its location. Our initial sample consists of the common stocks of all firms headquartered in Germany which have been listed on a German stock exchange at some point between June 13, 1988 and January 15, 2009.[3] The lower bound is determined by the availability of the daily number of shares traded. The upper bound is meant to maximize the sample size by the inclusion of Epiphany (January 6) in 2009. The data is then subjected to a three-stage screening process.[4] This leaves a final sample of 792 stocks, for which the appendix provides descriptive statistics at a weekly frequency. The mean (median) firm is in our sample for 556 (515) weeks, has an average market capitalization of 1,148 (123) million Euro, and has a weekly turnover of 1.42% (0.93%). There is large cross-sectional and considerable time-series variation in turnover, which again motivates the exploration of local bias as a potential driver of firm-level trading activity.

Figure 2.1 shows the geographic distribution of sample firms. Table 2.1 provides summary statistics for event study samples.

[3]See the appendix for an overview of all data sets used in this study. For the holidays analyzed here, the Frankfurt stock exchange has been open over the whole sample period, while stock trading at the regional exchanges in Germany started in 2000. This is unlikely to influence our results for three reasons. First, for all sample stocks, the primary exchange from which Datastream obtains its default prices turns out to be the Frankfurt stock exchange. Second, inferences remain unchanged if we restrict our analysis to those stocks which are exclusively traded on the Frankfurt stock exchange. Third, results are robust across time. In particular, they also hold for the subperiod 2000-2009 (see sections 2.4.2 and 2.4.3 for details).

[4]First, adjusted and unadjusted daily closing prices, market capitalization, book values, the number of daily shares traded, the number of total shares outstanding, adjustment factors as well as industry membership have to be available via Datastream. Second, we conduct the tests suggested by Ince and Porter (2006). Third, to assure that our analysis is not contaminated by very small and illiquid stocks, we exclude securities if their mean market capitalization is less than 10 million Euro or if the 5th percentile of their unadjusted prices is less than 1 Euro. The main results do not change if we use the sample after step two, which contains 1,071 stocks.

Figure 2.1: Geographic Distribution of Firm Headquarters and of Regional Holidays across Germany

This figure shows the location of firm headquarters across Germany. Headquarters are represented by black dots; additional clusters of headquarters (with more than 20 firms) in a given city are represented by larger dots and the corresponding number of firms. These clusters belong, from west to east, to the cities of Düsseldorf (28 firms), Cologne (36 firms), Frankfurt (40 firms), Stuttgart (21 firms), Hamburg (57 firms), Munich (70 firms) and Berlin (48 firms). Moreover, the figure exemplarily illustrates the geographic distribution of regional holidays across Germany. Shown is the example of Epiphany, which is legally recognized only in the grey-shaded states of Baden-Württemberg (118 firms), Bavaria (180 firms), and Saxony-Anhalt (3 firms).

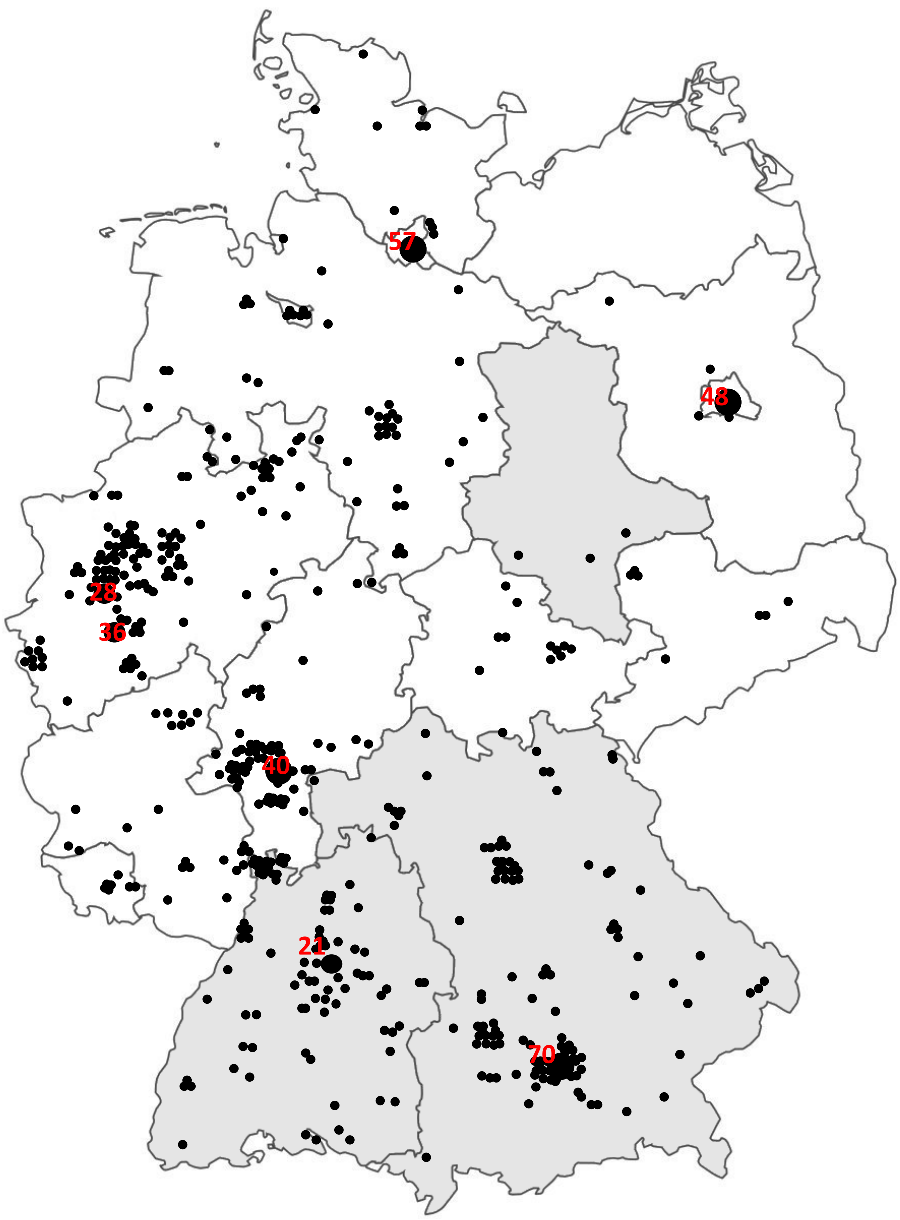


Table 2.1: Descriptive Statistics of Event Study Samples

This table provides summary statistics of event study samples for Epiphany (Panel A) and All Saints' Day (Panel B). *Holiday* ($Non - Holiday$) denotes the sample of firms whose headquarter is (not) located in a region where the respective holiday is legally recognized. $Median\ macap$ and *median daily return* refer to the cross-sectional median of time series averages of sample firms' market capitalization (in million Euro) and daily returns, respectively. *Industry Concentration* denotes the Herfindahl index, computed as the sum of squared industry group weights (Datastream Level 2 industry classification, 10 groups). Two versions are shown. In the equal-weighted version (EW), industry weights are determined by the percentage of sample industry group firms. In the value-weighted version (VW), industry weights are determined by the relative market capitalization of industry group observations, thereby excluding DAX30 firms. Table 2 of the appendix provides more detailed information about industry concentration and industry composition. DAX ($DAX/MDAX$) refers to the fraction of sample observations attributable to DAX30 (DAX30 and MDAX) firms in the period 1988-2009 (1994-2009). The MDAX comprises 50 large German companies from traditional sectors ranking immediately after the 30 DAX firms.

Panel A: Epiphany Sample					
Region	Number of firms	Median Macap	Daily median return	Industry Concentration EW (VW)	DAX (DAX + MDAX)
Holiday	301	1,037	-0.01%	0.15 (0.16)	6.1% (14.2%)
Non-Holiday	491	977	-0.01%	0.15 (0.16)	5.0% (15.0%)
Time-series properties of equally weighted turnover indices based on daily data					
Region	Mean	SD	5th Percentile	95th Percentile	Correlation (Holiday, Non-Holiday)
Holiday	0.21%	0.13%	0.06%	0.45%	0.86
Non-Holiday	0.20%	0.12%	0.07%	0.43%	
Panel B: All Saints' Day sample					
Region	Number of firms	Median Macap	Daily median return	Industry Concentration EW (VW)	DAX (DAX + MDAX)
Holiday	509	1,155	-0.01%	0.15 (0.17)	5.9% (14.9%)
Non-Holiday	283	704	-0.02%	0.16 (0.18)	4.3% (14.2%)
Time-series properties of equally weighted turnover indices based on daily data					
Region	Mean	SD	5th Percentile	95th Percentile	Correlation (Holiday, Non-Holiday)
Holiday	0.20%	0.12%	0.06%	0.44%	0.83
Non-Holiday	0.21%	0.13%	0.07%	0.46%	

Several findings highlight advantages of the German setting. First, both the treatment (holiday) and the control (non-holiday) groups form large portfolios. Second, their composition does not seem to differ much. For example, median firms have about the same market capitalization and comparable average stock returns. Industry concentration, as computed from Herfindahl indices based on Datastream Level 2 industry classification, is very similar. The appendix shows that also industry composition appears broadly comparable. Similar findings apply to the fraction of large firm observations. Third, the time-series properties of local turnover indices show a remarkably similar behavior, even in the tails of the distribution. Fourth, an eyeball analysis of figure 1 reveals that firm location in Germany tends to be less concentrated than in the predominantly used US samples (e.g. Ivkovic and Weisbenner (2005)). Fifth, not only firm-level variables, but also individual investors' characteristics seem comparable. This is suggested by calculations based on data of the German SAVE study (e.g. Boersch-Supan et al. (2009)), a comprehensive panel survey designed to provide representative information on the financial situation and relevant socio-psychological traits of German households. As can be seen from the following table, households' propensity to participate in the stock market, investors' risk taking behavior and economic expectations, their financial literacy and use of financial advice, or the influence of social contacts on financial decision-making is similar in control and treatment groups.

With regard to typical US samples of previous local bias studies, Seasholes and Zhu (2010) highlight a cross-sectional geographic sampling error, which they argue to potentially lead to incorrect conclusions. Taken together, the German setting seems to suffer less from this selection bias. Instead, portfolios are broadly diversified, homogeneous in several dimensions and thus seem particularly suitable for the following natural experiment.

2.4 Event Study

2.4.1 Methods and Baseline Results

In order to quantify the impact of localized trading, one needs to define a measure of trading activity. We focus on firm turnover as "turnover yields the sharpest empirical implications and is the most natural measure" (Lo and Wang (2000), p. 12).

Table 2.2: Individual Investor Characteristics in Holiday and Non-Holiday Regions

Calculations in this table are based on data from the German SAVE study, a rich panel survey produced by the Mannheim Research Institute for the Economics of Aging. It is designed to provide quantitative information on the economic situation and on relevant socio-psychological characteristics of a representative sample of German households. For a detailed description of the design and results of the SAVE study, we refer the reader to Boersch-Supan et al. (2009). Findings reported in the following table rely on data gathered in five consecutive yearly questionnaire studies with the same households, conducted between 2005 and 2009. The table summarizes various characteristics of individual investors in holiday and non-holiday regions for each of our three holiday samples (Epiphany, All Saints' Day, Corpus Christi). If not stated otherwise, the variables represent simple means or medians constructed from the pooled sample of all yearly surveys. Relying on various sets of weighting factors to recalibrate the sample with the aim of optimized representativeness does not change the qualitative nature of our findings. The computation of all variables (with the exception of "stock market participation") is conditioned on households who invest in the stock market (e.g. via individual stocks, but also via mutual funds, REITS etc.). In Panel B, subjects could give multiple responses. "No discussion of financial matters" refers to the fraction of subjects who stated to rely neither on relatives, friends, colleagues, neighbors nor financial advisers when dealing with financial matters. In Panel C, the extent to which the advise is followed is judged on a scale from 0 (not at all) to 10 (completely). In Panel D, "Objective financial knowledge" reports the fraction of participants who answered all of three financial literacy questions correctly. This variable is computed relying only on the questionnaire of 2009. The questions therein are designed to evaluate knowledge with regard to interest rates, inflation and risk of investment alternatives, respectively (see www.mea.uni-mannheim.de for details). "Self-assessed financial knowledge" gives respondents' statements regarding their subjective measure of financial knowledge on a scale from 1 (very low) to 7 (very high). In Panel E, "self-assessed risk-taking" is evaluated by asking subjects to assess the validity of the following statement on a scale from 0 (completely false) to 10 (completely true): "I do not mind taking risks in investments". "Expectations with regard to own future economic situation" are rated on a scale from 0 (very negative) to 10 (very positive).

Investor Characteristic	Epiphany		All Saints' Day		Corpus Christi	
	Holiday	Non-Holiday	Holiday	Non-Holiday	Holiday	Non-Holiday
Panel A: Financial Situation and Participation in the Stock Market						
Participation in the stock market?	26.35%	24.04%	25.81%	23.51%	25.80%	23.08%
Value of stock market investments in Euro (mean)	26,365	30,855	30,589	29,369	31,899	27,527
Value of stock market investments in Euro (median)	10,000	10,000	10,000	10,000	10,000	10,000
Total financial wealth in Euro (mean)	65,919	68,937	70,819	66,254	74,999	60,235
Total financial wealth in Euro (median)	36,000	32,849	32,075	34,488	34,000	33,000
Net monthly household income in Euro (mean)	3,079	2,988	3,099	2,932	3,156	2,828
Net monthly household income in Euro (median)	2,800	2,600	2,800	2,550	2,800	2,500
Panel B: Influence of Social Contacts (Excluding Professional Financial Advisors) on Financial Matters						
Discussion of financial matters with relatives?	28.61%	28.22%	28.41%	28.21%	27.17%	29.66%
Discussion of financial matters with friends?	23.12%	24.54%	23.18%	25.12%	23.28%	25.41%
Discussion of financial matters with colleagues?	7.82%	8.00%	7.19%	8.60%	7.16%	8.94%
Discussion of financial matters with neighbors?	0.64%	1.96%	1.37%	1.94%	1.63%	1.74%
No discussion of financial matters?	27.45%	28.09%	28.91%	27.14%	29.37%	26.25%
Panel C: Use of Financial Advice						
Discussion of financial matters with professional financial advisors?	50.14%	51.80%	51.19%	51.67%	50.73%	52.23%
If yes: Advice seeked at least once a month?	4.32%	2.65%	3.12%	2.88%	3.35%	2.57%
If yes: Advice seeked about four times per year?	23.26%	24.51%	24.21%	24.28%	23.61%	25.00%
If yes: Advice seeked about once a year?	49.51%	50.87%	50.66%	50.54%	50.73%	50.43
If yes: Advice seeked less than once a year?	22.91%	21.98%	22.01%	22.29%	22.31%	22.00%
If yes: To what extent is the advice followed? (mean, scale from 0 to 10)	6.04	6.08	5.98	6.14	6.02	6.13
If yes: To what extent is the advice followed? (median, scale from 0 to 10)	6	6	6	6	6	6
Panel D: Financial Literacy						
Objective financial knowledge (Top financial literacy score)	82.08%	78.59%	79.71%	79.10%	80.00%	78.59%
Self-assessed financial knowledge (mean, scale from 1 to 7)	4.97	4.93	4.89	4.97	4.91	4.97
Self-assessed financial knowledge (median, scale from 1 to 7)	5	5	5	5	5	5
Panel E: Self-Assessed Risk-Taking in Investments and Economic Expectations						
Self-assessed risk-taking in investments (mean, scale from 0 to 10)	2.99	3.02	3.04	3.00	3.06	2.97
Self-assessed risk-taking in investments (median, scale from 0 to 10)	2	2	2	2	2	2
Expectations with regard to own future economic situation (mean, scale from 0 to 10)	5.65	5.81	5.80	5.72	5.83	5.70
Expectations with regard to own future economic situation (median, scale from 0 to 10)	6	6	6	6	6	6

As turnover is naturally skewed, we use its natural logarithm in the following calculations. In the regression setting targeted at testing hypothesis 1, the dependent variable $TO_{i,t}$ is the daily turnover of firm i on a regional holiday at time t. We consider each year from 1988 to 2009 in which the holiday falls on a trading day. For All Saints' Day (Epiphany), this results in 16 (14) years with a total of 6,485 (5,657) observations.

During regional holidays, market turnover in general tends to be lower. The average daily turnover of a value-weighted (equal-weighted) turnover index during the whole sample period is 0.42% (0.20%). On Epiphany, these numbers decrease to 0.36% (0.14%), on All Saints' Day to 0.29% (0.13%). However, we are not interested in changes in trading activity per se, but in potential cross-sectional differences between holiday and non-holiday firms. Thus, the independent variable of interest is the holiday region dummy $Hol_{i,t}$ that equals one if a firm's headquarter is located in a holiday region and zero otherwise. The null hypothesis is that the dummy should not have any significance.

To isolate the holiday effect, it is essential to control for the expected level $E[TO_{i,t}]$ of turnover. To assure robustness, we rely on two models widely employed in previous research. Model 1 accounts for firm-specific average turnover in the pre-event period (e.g. Chae (2005)). In the baseline analysis, the expected firm turnover is calculated as the natural logarithm of the average turnover over t-20 to t-2. Model 2 controls for both market-related and firm-specific volume by adopting a "turnover market model"(e.g. Tkac (1999)). To this end, for t-60 to t-2, turnover for each firm is regressed on a market-wide, value-weighted turnover index $TO_{m,t}$. Using the coefficients from the time-series regression, expected turnover is then given by

$$E[TO_{i,t}] = \widehat{\alpha}_i + \widehat{\beta}_i TO_{m,t}. \tag{2.1}$$

As current firm-level turnover might be related to current stock return (e.g. Chordia et al. (2007)), we include two control variables. $Ret_{+,i,t}$ represents the event day stock return if positive and zero otherwise.[5] $Ret_{-,i,t}$ is defined analogously. This distinction is motivated by possible asymmetric effects caused by short-selling constraints or the disposition effect, which have been shown to affect localized trading (e.g. Grinblatt and Keloharju (2001)). It has also been documented that turnover is influenced by lagged

[5]However, our results do not change if we only include the lagged return or if we do not add return-related control variables at all. Moreover, as shown in section 2.4.2, inferences are the same when including interaction terms to allow for a different impact of returns on holiday firm turnover.

stock returns (e.g. Statman et al. (2006), Glaser and Weber (2009)). This effect should be captured at least partly by our measures of expected turnover. To more fully control for recent past returns, we include two analogous variables ($Ret_{+,i,t-1}$ and $Ret_{-,i,t-1}$) for the pre-event day return. The return controls might also be regarded as crude proxies for news or rumors, which could affect turnover. In section 2.4.3, we comprehensively test for differences in information release between holiday and non-holiday firms.

In our basic regression setting, we employ a Fama-MacBeth approach, combined with the method of West and Newey (1987). We implement the following cross-sectional model in each year and use the resulting time-series of coefficients to assess their significance:

$$TO_{i,t} = \beta_{0,t} + \beta_{1,t}E[TO_{i,t}] + \sum_{k=2}^{5} \beta_{k,t}ReturnControl_{k,i,t} + \beta_{6,t}Hol_{i,t} + \epsilon_{i,t} \tag{2.2}$$

Table 2.3 shows the findings for the Epiphany sample and the All Saints' Day sample, respectively. Displayed are results from three regression specifications, which differ in the dependent variable. The baseline regression uses firm-specific turnover at the day of the holiday ($TO_{i,t}$), the others use the day preceding and following the holiday, respectively.

The holiday region dummy attains a highly negative coefficient in all specifications. For both the Epiphany and the All Saints' Day sample, and for both models of expected turnover, the coefficient is strongly significant at the one percent level. The upper bounds of the 95% confidence intervals are all well below zero. Moreover, from an economic perspective, the effect is quite large: The pure holiday-induced abnormal drop in volume ranges from roughly 10% to slightly over 20%. Additionally, results are robust across time: In the Epiphany sample, the holiday region dummy is negative in each year; in the All Saints' Day sample, it attains a negative coefficient in about 80% of the observations. Finally, the holiday effect can, for the most part, only be identified at the day of the holiday itself. On the day before the holiday, there is no negative shock in trading activity; on the day after, there is some evidence, which, however, is much weaker than on the date of the holiday itself.[6] In sum, the findings so far support hypothesis 1.

[6] As unreported findings suggest, the effect on the day after the holiday might at least partly be attributable to the impact of bridge days as well as the end of Christmas holidays, which varies both across time and states, respectively. This seems also consistent with the anecdotal evidence given in footnote 2.

Table 2.3: Firm Turnover Around Epiphany and All Saints' Day: Yearly Fama-MacBeth Regressions

This table summarizes results from various regressions. The dependent variable is the natural logarithm of firm turnover on the day of (t), prior to $(t-1)$ or following $(t+1)$ the holiday. In Panel A and C, *expected turnover* is measured as the average firm turnover over t-20 to t-2. In Panel B and D, a market model of turnover calibrated from t-60 to t-2 is employed instead. $Ret_{+,t}$ ($Ret_{+,t-1}$) denote the stock return at t (t-1) if positive and zero otherwise. $Ret_{-,t}$ ($Ret_{-,t-1}$) are defined analogously. T-statistics (in parentheses) are computed with Newey/West (1987)-adjusted standard errors. Statistical significance at the ten, five and one-percent level is indicated by *, **, and ***, respectively. The reported R^2 is calculated as the average of adjusted R^2. *Predicted sign* denotes the fraction of a negative holiday dummy coefficient at t.

Panel A: Firm Specific Expected Turnover (N=5,657) Around Epiphany								
Dependent Variable	Constant	Expected Turnover	$Ret_{+,t}$	$Ret_{-,t}$	$Ret_{+,t-1}$	$Ret_{-,t-1}$	*Regional holiday dummy*	R^2
Firm turnover at t-1	-1.49*** (-6.13)	0.94*** (33.99)	11.00*** (8.49)	8.97** (2.71)	3.69 (1.25)	-1.65 (-0.42)	*-0.05 (-1.21)*	0.71
Firm turnover at t	-1.91*** (-6.77)	0.91*** (26.66)	19.25*** (4.28)	18.90*** (3.24)	4.63* (1.84)	-3.45 (-1.53)	*-0.23*** (-5.59)*	0.69
Firm turnover at t+1	-1.50*** (-6.32)	0.94*** (37.97)	16.54*** (6.09)	13.86*** (6.01)	5.38* (2.02)	4.70 (1.34)	*-0.10** (-2.40)*	0.71
Predicted sign							14/14	
95% conf. interval							-0.32 / -0.14	
Panel B: Market Model Expected Turnover (N=5,657) Around Epiphany								
Dependent Variable	Constant	Expected Turnover	$Ret_{+,t}$	$Ret_{-,t}$	$Ret_{+,t-1}$	$Ret_{-,t-1}$	*Regional holiday dummy*	R^2
Firm turnover at t-1	-0.64*** (-4.02)	0.96*** (83.87)	12.46*** (9.07)	11.64*** (3.52)	1.74 (0.82)	1.54 (0.42)	*-0.00 (-0.15)*	0.79
Firm turnover at t	-0.97*** (-5.60)	0.94*** (70.28)	19.41*** (4.85)	16.77*** (3.14)	5.20** (2.63)	-0.83 (-0.72)	*-0.18*** (-9.33)*	0.79
Firm turnover at t+1	-0.58*** (-3.82)	0.96*** (86.28)	16.59*** (6.18)	14.46*** (5.78)	5.86*** (3.12)	3.09 (0.97)	*-0.05* (-2.11)*	0.80
Predicted sign							14/14	
95% conf. interval							-0.22 / -0.14	
Panel C: Firm Specific Expected Volume (N=6,485) Around All Saints' Day								
Dependent Variable	Constant	Expected Turnover	$Ret_{+,t}$	$Ret_{-,t}$	$Ret_{+,t-1}$	$Ret_{-,t-1}$	*Holiday Region Dummy*	R^2
Firm turnover at t-1	-1.44*** (-8.84)	0.94*** (49.02)	15.05*** (5.57)	13.13*** (5.01)	2.81 (1.46)	0.90 (0.40)	*-0.00 (-0.11)*	0.76
Firm turnover at t	-2.64*** (-8.73)	0.85*** (23.76)	22.21*** (5.36)	20.09*** (5.01)	5.63*** (3.85)	-3.87 (-1.64)	*-0.13*** (-4.03)*	0.70
Firm turnover at t+1	-1.60*** (-8.02)	0.92*** (36.16)	13.74*** (4.88)	15.76*** (4.86)	8.98*** (3.04)	6.41*** (4.46)	*-0.06* (-1.80)*	0.75
Predicted sign							13/16	
95% conf. interval							-0.20/ -0.06	
Panel D: Market Model Expected Volume (N=6,485) Around All Saints' Day								
Dependent Variable	Constant	Expected Turnover	$Ret_{+,t}$	$Ret_{-,t}$	$Ret_{+,t-1}$	$Ret_{-,t-1}$	*Holiday Region Dummy*	R^2
Firm turnover at t-1	-0.58*** (-4.69)	0.96*** (65.99)	14.20*** (4.33)	15.53*** (4.90)	6.21*** (3.42)	0.87 (0.40)	*-0.04 (-0.76)*	0.80
Firm turnover at t	-1.72*** (-9.86)	0.88*** (59.10)	22.48*** (6.10)	20.02*** (5.80)	5.11*** (3.89)	-1.11 (-0.62)	*-0.16*** (-4.87)*	0.77
Firm turnover at t+1	-0.62*** (-5.64)	0.96*** (65.00)	14.19*** (4.01)	14.38*** (5.06)	6.80*** (3.43)	6.41*** (3.82)	*-0.10** (-2.64)*	0.80
Predicted sign							13/16	
95% conf. interval							-0.23/ -0.09	

2.4.2 Robustness Checks

The main results from a variety of sensitivity tests are summarized in table 2.4.

Our test specification might be misspecified in the sense that it may lead to a spurious positive factor loading on the holiday region dummy on average, irrespective of an actual holiday event. We therefore implement a “placebo treatment”: For each model specification and each holiday sample, we randomly select 500 days (excluding the period from t-1 to t+1, where t denotes the holiday) and, for each of these pseudo events, run the regression as given in Equation (2). Mean and median factor loadings on the holiday region dummy are given in panel A. In all specifications, they are virtually zero.

There is arguably some element of arbitrariness in the length of the pre-event period in both models of expected turnover. Therefore, we experimented with intervals from 10 to 100 trading days. Panel B verifies that inferences remain the same.

It might be possible that the importance of the return controls varies between holiday and non-holiday firms. We thus interact all return variables from the baseline regression with the regional holiday dummy. It turns out that none of them is significant. Panel C shows that the importance of the holiday region dummy remains unaffected.

One might be concerned that the results could partially be driven by a disproportionate number of holiday firms whose stocks are not traded at the event day. Our findings might then not reflect a broader phenomenon, but rather be attributable to outliers. We thus repeat the analysis discarding all stocks with zero trading volume. However, as shown in panel D, this exercise rather strengthens our results.

Panel E shows results when using raw (instead of logarithmized) turnover. In all specifications, the holiday effect is significant at the 1% level. Moreover, it keeps its economic significance. For the mean (median) firm the results indicate a pure regional holiday-induced drop in daily trading volume of roughly 200,000 (more than 20,000) Euro.

Residuals of a given firm might be correlated across years, potentially leading to biased standard errors. We thus follow a suggestion of Petersen (2009) by pooling all firms with non-zero turnover, adding year dummies and clustering standard errors by firm. As shown in panel F, findings are robust to this alternative econometric specification.

Table 2.4: Robustness Checks

This table displays the coefficient in front of the holiday dummy obtained from various regressions to test for the robustness of our baseline results. T-statistics are reported in parentheses. Statistical significance at the ten, five and one-percent level is indicated by *, **, and ***, respectively.

	Epiphany	All Saints' Day
Panel A: Mean and Median Factor Loadings on the Regional Holiday Dummy from Placebo Treatments		
Firm specific expected turnover	Mean: -0.001, Median: -0.004	Mean: 0.005, Median: 0.001
Market model expected turnover	Mean:0.007, Median: 0.009	Mean: 0.005, Median: 0.006
Panel B: Alternative Pre-event Periods		
Firm specific expected turnover in t-10 to t-2	-0.24*** (-5.54)	-0.13*** (-3.45)
Firm specific expected turnover in t-40 to t-2	-0.21*** (-5.02)	-0.14*** (-3.78)
Firm specific expected turnover in t-40 to t-11	-0.20*** (-5.28)	-0.15*** (-4.14)
Market model expected turnover in t-100 to t-2	-0.17*** (-7.20)	-0.17*** (-3.70)
Market model expected turnover in t-40 to t-2	-0.19*** (-9.04)	-0.16*** (-5.41)
Market model expected turnover in t-60 to t-11	-0.17*** (-9.12)	-0.16*** (-4.62)
Panel C: Interacting Return Variables with Holiday Dummies		
Firm specific expected turnover	-0.29*** (-4.29)	-0.17*** (-2.82)
Market model expected turnover	-0.22*** (-5.69)	-0.21*** (-3.54)
Panel D: Omitting Stocks With Zero Trading Volume on Event Day		
Firm specific expected turnover	-0.24*** (-11.48)	-0.15*** (-4.84)
Market model expected turnover	-0.20*** (-15.10)	-0.19*** (-6.23)
Panel E: Using Ordinary Turnover		
Firm specific expected turnover	-0.02%*** (-3.80)	-0.02%*** (-3.10)
Market model expected turnover	-0.02%*** (-3.31)	-0.02%*** (-3.82)
Panel F: Pooled Regression With Year Dummies and Standard Errors Clustered by Firm		
Firm specific expected turnover	-0.23*** (-4.73)	-0.13** (-2.51)
Market model expected turnover	-0.19*** (-4.13)	-0.16*** (-2.86)
Panel G: Analysis Based on Metropolitan Areas		
Firm specific expected turnover	-0.22*** (-9.46)	-0.13*** (-4.13)
Market model expected turnover	-0.18*** (-5.90)	-0.17*** (-4.77)
Panel H: Regional Holiday Effects on Corpus Christi (Since 2000, Econometric Approach as in Panel F)		
	Firm specific expected turnover	Market model expected turnover
	-0.20*** (-2.67)	-0.20*** (-3.61)
Panel I: Carnival Monday		
	Firm specific expected turnover	Market model expected turnover
	-0.05** (-2.38)	-0.06** (-2.74)

Legally recognized regional holidays are observed on a state level. Thus, our interpretation rests on the idea of states being an appropriate classification of the preferred investment habitats of local investors. While similar concepts have been proven fruitful in US studies (e.g. Hong et al. (2008), Korniotis and Kumar (2010)), it is clearly only a noisy proxy. Note, though, that this works against detecting a regional holiday effect: If local investors tilted their trading towards stocks of local firms irrespective of state borders, then it would be hard to identify differences in trading activity between two neighboring states. In an attempt to use a classification scheme with a more pronounced socio-economic background, we repeat our analysis building on metropolitan areas as defined by the Conference of Ministers for Spatial Planning.[7] Some areas span more than one state, whereas some states contain more than one metropolitan region. Panel G verifies that the coefficient is sporadically estimated even marginally more precisely, possibly pointing to the true impact of localized trading being stronger than reported.

We also study turnover shocks on Corpus Christi as the third legally recognized regional holiday. It is celebrated in the states of Baden-Württemberg, Bavaria, Hesse, North Rhine-Westphalia, Rhineland-Palatinate and Saarland, at the Thursday 60 days after Easter Sunday. Stock market trading on this day started not before 2000, which results in a total of 5,078 firm-level observations distributed over nine yearly observations. Panel H verifies that our findings hold also in this case. The shock in turnover is highly significant, and estimated to be close to 20%. The setting for Corpus Christi is, apart from the shorter sample period and the fixed day of the week, not conceptually different from Epiphany and All Saints' Day. Including all holidays in the remaining tests increases the sample size and ensures that we consider each regional holiday in Germany for which requirements on a meaningful event study are met.

However, if our results were representative of a widespread localized trading phenomenon, then we might also detect similar patterns in related scenarios such as Carnival. While there is no official holiday, representative surveys reveal that Carnival is prominent in some (mostly southern and western) regions, but rather unpopular in other (mostly northern

[7]This classification identifies eleven metropolitan regions in which roughly 70% of the German population and 84% of sample firms are located. http://www.eurometrex.org defines these areas as "larger centres of economic and social life" containing "core business, cultural and governmental functions". We only consider areas clearly belonging either to a holiday or a non-holiday region. This leaves a total of 5,416 (4,350) observations for the All Saints' Day (Epiphany) sample.

and eastern) areas of Germany.[8] Despite the lack of clear-cut separation between affected and non-affected regions, we run an analogous analysis for Carnival Monday, on which most parades are held. Panel I provides evidence supportive of our line of reasoning.

2.4.3 Differences in Information Intensity?

A key concern to a local bias story is that holiday firms might simply release less information than otherwise comparable non-holiday firms. To the extent that this triggers rebalancing trades or increased differences of opinion, it might partly explain our findings. As an intuitive and rather informal first approach to explore the possibility of such an information effect, we compare the fraction of corporate news released around the holiday. To this end, we rely on firm-specific news stories published by DGAP, a German news agency, from January 2000 to January 2009. These news include time-stamped ad hoc disclosures, by which German firms are forced to publish new value-relevant information immediately. We manually collect these disclosures for each sample firm. The database additionally covers a broad range of other news, such as directors' dealings or business reports. Since data retrieval is labor intensive, we gather these corporate news for half of sample firms, which we randomly select. The following test is based on this subsample.

We create a dummy variable that states for each firm and each day whether corporate news or ad hoc disclosures have been released. Then, for each holiday, and separately for the holiday and the non-holiday sample, we compute the fraction of all news attributable to a short window around the holiday (t-1 to t+1). After that, we compute an odds ratio by dividing the percentage obtained for the holiday sample by the percentage obtained for the non-holiday sample. If holiday firms released temporarily less news, we would expect values persistently well below one. However, the odds ratios are 1.05 for Epiphany, 1.02 for All Saint's Day and 0.84 for Corpus Christi, pointing against a widespread drop in news release. As later sections of this study reveal that firm size is an important determinant of

[8] We here rely on survey results published in the magazine "Daheim in Deutschland" (by Reader's Digest), February 2010. Our classification is based on the fraction of individuals stating to actively participate in carnival celebrations. The areas of Hesse, Rhineland Palatinate, Saarland (roughly 30%), Bavaria (27%), Baden Württemberg (25%) and North Rhine-Westphalia (24%) serve as a treatment group. The remaining regions have participation rates between 10% and 19% and thus serve as a control group. A related classification scheme based on the relative popularity of carnival clubs leads to similar results. Data for this analysis is provided by "Bund Deutscher Karneval", the umbrella organization of several thousand German carnival clubs.

the drop in trading activity, we determine whether this might be due to differences in news release. Specifically, we repeat the analysis separately for large and small stocks, split by the median of market capitalization at the beginning of the year. Around Epiphany, there are no marked differences. Around All Saint's Day, small holiday firms appear to release relatively more news than large holiday firms. Around Corpus Christi, this picture partly reverses. In sum, there is no clear pattern.

For deeper insights, we test more rigorously for differences in news arrival from four further perspectives. Specifically, we study cross-sectional shocks with regard to abnormal price movements, with regard to the degree of analyst coverage, with regard to investors' internet search behavior as well as with regard to firms' media exposure. In the following, these tests, whose main results are presented in tables 2.5 and 2.6, are described in detail.

Firm-specific news are likely to affect the magnitude of abnormal returns. Firm-specific information should manifest itself in an increased importance of the idiosyncratic component of the firm's daily stock return. On the other hand, if there is hardly any new information, then the return should primarily be driven by the stock's exposure to pervasive well-known risk factors. Thus, if there was indeed temporarily less news for the typical holiday firm, we would expect its absolute abnormal return to be considerably lower than during some control period on average. For the typical non-holiday firm, however, there should be no or at least not as much of a difference. A benefit of this approach is that shock variables can be computed continuously, providing data for each firm on each day. This overcomes the problem that official news coverage of a given firm may be sporadic, even though there might be rumors, speculation or private information investors react on. To formalize the cross-sectional prediction as sketched above, we employ the following procedure. First, for each firm and each day, we compute the abnormal stock return. By employing both a market model and a Carhart (1997) four factor model, we follow standard event study methodology; due to very similar findings, only the findings from the latter model are reported. The four factor model is based on German data and includes the market, size and value factors in the spirit of Fama and French (1993) and the momentum factor as constructed in Carhart (1997). The appendix provides more detailed information about the construction of the factors. Second, for each firm, we compute the difference between the absolute abnormal return on the day of the holiday (=t) and the average absolute abnormal return in some control period. We here rely on the period from

Table 2.5: Tests for Cross-Sectional Differences in News Arrival

This table summarizes results from various tests aimed at detecting potential cross-sectional differences in news arrival between holiday and non-holiday firms at the day of the holiday (=t). *Large firms* (*Small firms*) refer to stocks with a market value larger (smaller) than the median stock, measured at the beginning of the year. Statistical significance at the ten, five and one percent level is indicated by *, **, and ***, respectively. Panel A reports differences in shocks in absolute abnormal returns. To this end, daily absolute abnormal returns for each firm during t-5 to t+5, as obtained from a German version of the Carhart (1997) four factor model, are computed. Factor loadings are estimated from time-series regressions from t-66 to t-6. For both the holiday and the non-holiday sample, firm-specific shocks are computed as the absolute abnormal return at t minus the average absolute abnormal return in t-5 to t+5 (excluding t). The table reports the difference between the median shock value for the holiday sample and the median shock value for the non-holiday sample, averaged across years. Statistical significance is assessed by bootstrapping as described in footnote 11. Panel B reports the coefficient in front of the regional holiday dummy as obtained from pooled regressions of daily firm-specific abnormal search volume in Google on dummies for regional holidays, years and industry groups. Abnormal search volume is computed as the difference between the search volume at t and the average search volume in t-10 to t-2, divided by the standard deviation of search volume in this pre-event period. T-statistics are reported in parentheses. The last column reports p-values as obtained from an F-test of joint significance of all three holiday dummies. Panel C shows the average fraction of total analyst recommendations and reviews attributable to holiday firms at t. Only recommendations and reviews issued (not outstanding) on a given day are considered. In a similar way, the fraction holiday firms account for is also computed for every other day in t-5 to t+5. These values are pooled to construct an empirical benchmark distribution of analyst coverage in a nearby period. Values in parentheses represent the percentiles of this distribution as achieved at t. A higher percentile indicates that holiday firm recommendations account for a larger fraction of the total number of recommendations. In the value-weighted (equal-weighted) analysis, multiple recommendations of the same firm are considered as multiple observations (single observation).

Panel A: Differences in Shocks in Absolute Abnormal Returns				
Dependent Variable	Epiphany	All Saints' Day	Corpus Christi	Pooled
Difference in shock variable: All firms	-0.05%*	-0.02%	-0.02%	-0.03%
Difference in shock variable: Large firms	-0.07%*	-0.01%	0.01%	-0.03%
Difference in shock variable: Small firms	-0.02%	-0.05%	-0.03%	-0.03%
Panel B: Abnormal Search Frequencies for Firm Names in Google				
Dependent Variable	Epiphany	All Saints' Day	Corpus Christi	P-value joint sign.
Shocks in online search queries: All firms	-0.13 (-0.61)	-0.15 (-1.40)	-0.19 (-1.42)	0.17
Shocks in online search queries: Large firms	-0.26 (-0.52)	-0.33 (-1.02)	-0.20 (-0.40)	0.19
Shocks in online search queries: Small firms	-0.12 (-0.58)	-0.16 (-1.55)	-0.08 (-1.14)	0.16
Panel C: Fraction of Holiday Firm Analysts Recommendations				
Dependent Variable	Epiphany	All Saints' Day	Corpus Christi	
Value-weighted fraction of recommendations	40.34% (64)	68.57% (59)	81.51% (40)	
Equally-weighted fraction of recommendations	40.37% (58)	69.90% (62)	82.57% (43)	
Value-weighted fraction of reviews	41.67% (66)	63.64% (40)	87.87% (54)	
Equally-weighted fraction of reviews	43.08% (72)	63.84% (44)	89.23% (54)	

Table 2.6: Media Coverage and the Regional Holiday Effect

Panel B shows the average fraction of news stories for holiday firms on t-1, t (the holiday) and t+1. This fraction is also computed for every other day of the year, giving rise to a benchmark distribution. Percentiles obtained for t-1, t and t+1 are reported in parentheses. A higher value indicates that holiday firms account for a larger fraction of total coverage. *Large firms* (*Small firms*) refer to stocks with a market value larger (smaller) than the median stock. Panel C reports the interaction effect, computed as in Ai and Norton (2003), obtained from probit regressions of press coverage on the regional holiday dummy, the event date, holiday dummy*event date, and year dummies. Panel D shows the coefficients for the holiday dummy, as obtained by the baseline pooled regression (see section 2.4.2) plus a set of dummies for daily press coverage and ad hoc disclosures within t-5 to t+5. Statistical significance at the ten, five and one percent level is indicated by *, **, and ***, respectively.

Panel A: Descriptive Statistics (January 1, 2000 - January 15, 2009)

Newspaper	Total number of news stories	Coverage		Pairwise Firm-Level Correlation in Media Coverage		
				Handelsblatt	SZ	FTD
Handelsblatt	61,956	90.34%	Handelsblatt	1	0.23***	0.20***
SZ	34,497	79.42%	SZ	0.23***	1	0.19***
FTD	29,672	73.44%	FTD	0.20***	0.19***	1
All	126,125	93.77%				

Panel B: Fraction of News Stories about Holiday Firms Around the Holiday (=t, Percentiles in Parentheses)

Holiday	value-weighted		equal-weighted	
	t	t+1	t	t+1
Epiphany: All firms	30.19% (88)	22.91% (14)	32.41% (89)	27.05% (53)
All Saints' Day: All firms	55.83% (3)**	55.85% (3)**	59.33% (4)**	59.28% (3)**
Corpus Christi: All firms	81.68 (39)	82.63% (46)	81.21 (34)	81.32% (34)
Epiphany: Large firms	30.02% (89)	22.11% (14)	31.55% (87)	26.12% (45)
All Saints' Day: Large firms	55.33% (4)**	55.64% (4)**	58.56% (3)**	59.78% (4)**
Corpus Christi: Large firms	82.35 (37)	82.48% (37)	82.01 (35)	81.52% (34)
Epiphany: Small firms	33.33% (55)	29.41% (44)	33.33% (55)	29.41% (44)
All Saints' Day: Small firms	71.43% (53)	57.14% (20)	64.69% (43)	57.14% (20)
Corpus Christi: Small firms	66.67 (38)	82.98% (72)	66.67 (38)	82.98% (72)

Panel C: Marginal Effects of Probit Regressions Around the Holiday (=t, z-values in Parentheses)

Holiday	t-1	t	t+1
Epiphany	-0.41% (-0.69)	0.70% (1.16)	-0.03% (-0.05)
All Saints' Day	-0.01% (-0.02)	-1.17%** (-2.15)	-1.16%* (-1.86)
Corpus Christi	0.35% (0.71)	-0.33% (-0.60)	-0.80% (-1.35)

Panel D: Pooled Regression (2000-2009) with Controls for Media Coverage and Ad Hoc Disclosures (t-statistics in Parentheses)

	Epiphany	All Saints' Day	Corpus Christi
Firm-specific expected turnover	-0.20*** (-3.86)	-0.11** (-1.98)	-0.16** (-2.16)
Market model expected turnover	-0.19*** (-3.58)	-0.12** (-2.22)	-0.17** (-2.23)

t-5 to t+5 (excluding t), but results are not sensitive to this choice. The resulting variable has the interpretation of an unexpected change in the relative importance of idiosyncratic stock return factors. Third, for both the holiday and the non-holiday sample, we rank firms based on this shock variable. We take the cross-sectional median for both samples to get an estimate of the shock for the typical firm.[9] Fourth, we compute the cross-sectional difference between the median shock for the holiday sample and the median shock for the non-holiday sample. A news-based explanation of our findings would predict values significantly below zero, as the shock in the relative importance of firm-specific return factors for the typical holiday (non-holiday) firm should be more (less) negative. We repeat the procedure in each year. Finally, a bootstrap approach[10] is used to test whether the average of the resulting time series of differences is statistically distinguishable from zero. However, panel A of table 2.5, which reports results for the Epiphany, All Saints' Day as well as Corpus Christi sample, shows that this not the case. The only slightly significant event is on the day of Epiphany, where, from an economic perspective, the resulting return difference appears small. For all other holidays, differences are very close to zero and insignificant, implying that in most cases shocks in abnormal returns do not differ much between holiday and non-holiday firms. Pooling observations does not lead to different conclusions. Moreover, there are no persistent differences for large and small stocks, again split by the median of market value.

Our second test is inspired by Da et al. (2011) and based on cross-sectional shocks in search frequencies for firm names in Google. The application "Google Insights for Search" allows to construct standardized time-series of terms entered in the internet search engine. Data is available on a daily basis from January 2004 on. Computing shocks in search volume might be regarded as a possibility to quantify unexpected changes in revealed (and thus direct) focus to individual firms, induced by some external stimulus. In this sense, changes

---

[9]The appendix provides more details about the distribution of shock variables. It verifies that findings are qualitatively similar when relying on the mean (instead of the median) of the winsorized cross-section. It also shows that extreme return events are only slightly more frequent for non-holiday firms.

[10]The comparison of shock variables results in a holiday-specific time series of differences between holiday and non-holiday firms. We use this data to simulate 10,000 pseudo time-series of the same length as the original sample by randomly drawing values with replacement. Averaging values separately for each pseudo time-series yields 10,000 pseudo estimates of the difference in median shock variables. Finally, we assess whether the value obtained from the averaged original time-series is reliably negative by computing the fraction of simulated estimates that take on values below zero. For a discussion of simulations in event studies, see e.g. Lyon et al. (1999).

in the query frequency of a firm name[11] appear a promising way of capturing shocks in the arrival of firm-specific news or rumors. For example, Da et al. (2011) report a positive correlation between search volume shocks and traditional proxies for information release, such as extreme returns and news stories. The authors show that internet search volume even often leads alternative measures of news arrival. We thus construct a measure of unexpected search behavior for each firm based on daily data. It is defined as the difference between the search frequency during the holiday (=t) minus the average frequency over t-10 to t-2, divided by the standard deviation in this pre-event period. We then pool observations and regress the shock variables on a holiday region dummy in addition to controls for years and industries. We do so for the sample of all firms, of large firms, and of small firms. Panel B of table 2.5 shows that all holiday region dummy coefficients are insignificant, both separately and jointly, pointing against a news-based story.

Our third analysis focuses on the large effort of analysts in collecting, processing and disseminating information (e.g. Womack (1996)). We are interested in whether aggregated analyst coverage during regional holidays differs from coverage in a nearby benchmark period. Specifically, we concentrate on the number of daily analyst recommendations issued, and determine whether the fraction holiday firms account for is exceptionally low during the holiday. This is what a news-based explanation of our findings would arguably predict. To test this hypothesis, we match our sample with the I/B/E/S analyst buy/hold/sell-recommendations database. This results in a total of 51,497 stock recommendations of 196 brokers, which cover more than 80% of the sample firms. For the eleven day period centered around the holiday (t-5 to t+5), we then determine which fraction of all recommendations issued on this day is attributable to holiday firms. The length of this benchmark period is meant to account for the seasonality in earnings reports, but the qualitative nature of our findings is robust to alternative control windows. We average values for t. Values for the benchmark period (excluding t) are pooled to give rise to an

[11] One might be concerned about the use of firm names. They might not be unambiguous and a few of them clearly have multiple meanings. However, this seems unlikely to drive our main results. First, we study differences between two large samples with several hundred firm names. Thus, any potential inaccuracies and inconsistencies are likely to cancel out. Second, we are interested in shocks of search frequencies, i.e. we control for the expected level of queries. Third, "Google Insights for Search" additionally provides a top search list with the terms most closely related to the original search. In an attempt to manually cleanse the data, we used that information to exclude those firms that seemed most likely to distort the analysis. Inferences remained unchanged. The alternative of relying on security identification numbers instead of firm names turned out to be unproductive as search frequencies tend to be much lower, resulting in many missing values.

empirical benchmark distribution of relative analyst coverage for holiday firms. Relying on the percentiles of this distribution, we are able to detect whether analyst information transmission for holiday firms exhibits a negative shock. We distinguish between a value-weighted analysis, in which multiple recommendations made for the same firm on the same day are considered as multiple observations, and an equal-weighted analysis, in which we regard such a scenario as a single observation. The latter tends to give more weight to small firms, which less often receive several recommendations at the same day. As a sensitivity check, we repeat the analysis now focusing on the review date, i.e. the most recent date that an estimate is confirmed by an analyst to I/B/E/S as accurate. Panel C of table 2.5 shows the fraction of total analyst coverage on the event day. Percentiles are given in parentheses. A higher percentile indicates that holiday firm recommendations account for a larger fraction of the total number of recommendations issued. In all specifications, coverage does not seem to decrease for firms located in holiday regions. Judging from the percentiles of the distribution, the holiday rather appears like an average day of the benchmark period.[12] Moreover, the value-weighted and the equal-weighted analysis show a similar picture, suggesting there are no marked differences between large and small firms.

As a final test, we study shocks in media coverage in three leading German daily business newspapers, which are published nation-wide.[13] The comprehensive database, for which panel A of table 2.6 gives more details, is based on daily data from January 1, 2000 on and comprises Financial Times Deutschland, Handelsblatt and Sueddeutsche Zeitung. Searching factiva and genios, articles about each firm for each day and in each paper are manually collected.[14] This results in a total of 126,125 news stories covering almost 94% of our sample firms. Again, we distinguish between a value-weighted and an equal-weighted

[12] One might be concerned about noise in the data. Indeed, a similar bootstrapping approach as outlined in footnote 11 reveals that the dispersion of simulated outcomes is quite substantial. However, even the lower bound of the 99% confidence interval does not touch the 10th percentile of the benchmark distribution, which contradicts an information-based story.

[13] IVW, a German auditing institution that provides data on the distribution of media products, reports that Sueddeutsche Zeitung had the second highest circulation among nationwide published daily papers over the period 2000 to 2008. It ranks first if one excludes the popular press. Among the daily newspapers with a strong focus on business and economics, Handelsblatt and Financial Times Deutschland rank first and second. In the fourth quarter of 2008, the three newspapers had a combined circulation of more than 800,000 copies per day.

[14] Similarly as in Tetlock et al. (2008), we thereby require the article to mention at least twice the name or security identification number of the firm. This procedure aims at reducing noise and identifying relevant firm-specific articles. Coverage for Financial Times Deutschland starts on January 1, 2001.

analysis. The latter relies on a dummy variable that simply states whether a firm has received press coverage on a given day. The former individually counts each article. It thus takes on values greater than one if there are several firm news stories in the same paper, or if several papers cover the firm. In doing so, it tends to give more weight to blue chips and big news. For further insights, we additionally split firms into large and small stocks, as before. Across all specifications, there is considerable variation in daily media coverage. For instance, on a given day, the fraction of news stories attributable to firms that didn't make the news the day before, is 63% (52%) for the equal-weighted (value-weighted) analysis on average. Focussing on small firms yields even 91% (90%).

Panel B shows results from a test similar to the one used for analyst coverage. We analyze whether aggregated media coverage for holiday firms is abnormally low around the holiday. We consider both the event day and the following day, as information becoming public at t can not be published by newspapers before t+1. To assess statistical significance, we calculate the percentage of total media coverage attributable to holiday firms for each day of the year.[15] We then analyze the fraction of press coverage around the holiday relative to the whole empirical distribution, which does not exhibit strong seasonal patterns. The analysis produces mixed results. Around All Saints' Day, media coverage for holiday firms is indeed significantly lower, which, in line with findings from the test on corporate news releases, appears to be driven by larger firms. However, there is no similar evidence for any of the other holidays. In fact, press coverage is sometimes even higher than on average. In the overall picture, results point against a strong general drop in media exposure for both large and small holiday firms. To gain more insight, we implement a more formal regression approach. We create the dummy $News_{i,t}$ which indicates for each firm i on each day of the eleven trading days period centered around the regional holiday whether a news article was published.[16] We then pool the observations and run the following probit

[15] We thereby account for the fact that not all newspapers are published at each day of the year: At Corpus Christi, Handelsblatt and Sueddeutsche Zeitung are not distributed. At Epiphany, Sueddeutsche Zeitung is not published. This is unlikely to materially influence our analysis. First, for the more important date t+1, all newspapers are available. Findings are similar as on date t. Second, the results from the equally- and from the value-weighted analysis are similar in general. This suggests that relevant information is, for the most part, picked up by each of these leading newspapers so that partly relying on a subset of them does not change the qualitative nature of the results. This line of reasoning is also supported by the highly significant correlations in daily firm-level media coverage as shown in panel A of table 2.6.

[16] We choose this binary approach to reduce the overcounting of news about the same subject from multiple sources. However, an analysis focussing on the actual number of news produces very similar results. The eleven day period is largely representative for the media coverage in the whole year.

regression separately for Epiphany, All Saints' Day and Corpus Christi:

$$NEWS_{i,t} = \beta_0 + \beta_1 EventDummy + \beta_2 HolidayRegionDummy + \beta_3 InteractionTerm + YearDummies + \epsilon_{i,t} \tag{2.3}$$

The event dummy indicates the holiday within the event period. We also run analogous regressions for the days preceding and following the holiday. Of interest is the interaction effect between the event dummy and the holiday region dummy. If the volume shock was a result of systematic cross-sectional differences in press coverage, then it should consistently attain a significantly negative sign. Panel C of table 2.6 reports results from the nine probit regressions. Magnitude and significance of the interaction effect are assessed as suggested by Ai and Norton (2003). Again, the only significant results are found for the All Saints' Day sample. Thus, the findings at best sporadically point to differences in information release picked up by the press.

We finally incorporate additional control variables in our pooled regression approach as outlined in section 2.4.2. For data availability reasons, we focus on the period from 2000 to 2009, and add a set of dummies to control for the effect of media coverage and ad hoc disclosures on any day between t-5 and t+5. Panel D of table 2.6 reveals that the regional holiday effect keeps its significance, both from an statistical and an economic point of view. Modifying the analysis by focussing only on those stocks for which we have additional information about the release of other corporate news yields similar results.

Taken together, the combined findings from all tests in this section provide the following picture: First, we cannot dismiss the hypothesis of lower information intensity for holiday firms as there is minor evidence of differences in news release. Their lack of robustness and small magnitude, however, suggest they are unlikely to fully explain the economically substantial and pervasive drop in trading volume for holiday firms. The evidence points against persistent disparities between small and large firms. Second, controlling for potential differences in news arrival to the extent possible, our results remain qualitatively unchanged. Third, these findings strongly confirm hypothesis 1.

2.5 Determinants of the Regional Holiday Effect

Firm characteristics What factors drive the cross-sectional heterogeneity in negative turnover shocks? To answer this question, we first construct a firm-specific measure of abnormal turnover, defined as actual (logarithmized) turnover during the holiday minus the average turnover during t-20 to t-2. For robustness reasons, we then run pooled regressions separately for each of the three holiday samples as well as for two sample periods.

Hypothesis 2, inspired by the model of Merton (1987), posits that the turnover shock should be particularly strong if a firm is visible primarily to local investors. Merton argues that investor recognition is a function of the shadow cost of information, which, in his model, depends on idiosyncratic risk, relative market size and the completeness of the shareholder base. We thus use the logarithm of a firm's market capitalization, as measured at the end of the preceding year, and a firm's idiosyncratic risk as independent variables. Idiosyncratic risk is defined as the standard deviation of the residual obtained by fitting a Carhart (1997) four factor model (as described in section 2.4.3) to the daily return time-series from t-180 to t-6.

Market capitalization is strongly negatively related to the total number of shareholders (e.g. Grullon et al. (2004)) and positively related to the fraction of local investors (e.g. Zhu (2003)). Consequently, we expect a smaller drop in volume for larger firms, which implies a positive coefficient for firm size. Idiosyncratic risk, on the other hand, increases the shadow cost of information. Local investors are commonly thought to possess (actual or perceived) informational advantages. Thus, local clienteles should account for a relatively large proportion in the trading of stocks with high idiosyncratic risk, which should go along with a more pronounced negative volume shock during regional holidays. Consequently, a negative coefficient is expected.

In addition, we employ with residual media coverage a third proxy, which is orthogonal to size and available for the years 2001 to 2009. The residual is obtained from yearly cross-sectional regressions of the number of firm-specific press articles in the previous year on its lagged average market size, turnover and absolute return as well as on a set of control variables for industry and DAX30 membership. Press articles are taken from the comprehensive media coverage database described in section 2.4.3. Residual coverage is designed to proxy for the unexpected high or low weight the media attaches to a certain firm. Given the importance of leading business newspapers in disseminating information to a broad audience, residual media coverage is an intuitive measure of firm visibility. Consequently, we expect a positive coefficient.

Previous research and our baseline analysis highlighted the importance of current returns for current turnover. We thus include the same two return-based variables in the regression. To control for additional effects induced by medium-term return continuation, we consider the loading on the momentum factor (WML), obtained from a regression of stock returns on the Carhart (1997) four factor model. The loadings on the market as well as value factor ($RMRF$, HML) are considered as proxies for systematic risk (e.g. Chordia et al. (2007)). The intercept from this regression (*Alpha*) is included as it has been argued to contain a premium related to liquidity or heterogeneous information (e.g. Lo and Wang (2000)). Moreover, we include a rural dummy for firms located outside a metropolitan region. The "only game in town effect" (Hong et al. (2008)) suggests a negative coefficient. Inspired by e.g. Seasholes and Wu (2007), a 52 week high dummy for stocks whose price has exceeded this bound in the previous week is considered. Finally, we include a set of industry dummies.

For each holiday, table 2.7 displays univariate and multivariate results for the whole sample period. We report coefficients for the subperiod 2001 to 2009 separately. These coefficients additionally include residual media coverage and controls for the availability of press articles as well as ad hoc disclosures around the event date (see also section 2.4.3). The findings are broadly consistent with our expectations. Investor recognition seems an important driver of the turnover shock. All proxies consistently attain the predicted sign and, with the exception of idiosyncratic risk, are persistently statistically significant. The effect of market capitalization is clearly the strongest, but residual media coverage has an incremental effect. The magnitude of the results is also of economic importance: As a rough estimate, for example, a one standard deviation change in firm size has a similar impact as a one standard deviation change in stock return. The current absolute return is highly significant. The dummies for rural firms and the 52 week high attain coefficients as predicted, but their importance is not robust. The other controls seem to play only a minor role. In sum, hypothesis 2 can broadly be confirmed. The regional holiday effect is considerably stronger for firms less visible to non-local investors.

Table 2.7: Determinants of the Regional Holiday Effect

This table summarizes the main results obtained from pooled regressions of firm-specific abnormal turnover on the date of a regional holiday (=t) on a number of explaining variables. Only firms whose headquarter is located within the region where the holiday is legally recognized are included. The independent variables include return controls (see table 2 for a detailed description); the log of lagged firm market capitalization; idiosyncratic risk; residual media coverage; the loadings on the market, value and momentum factor (RMRF, HML, WML, respectively); the intercept from that regression (Alpha); a rural dummy; a 52 week high dummy; controls for media coverage and ad hoc disclosures around the event; a set of 10 industry dummies obtained from the Datastream level 2 industry classification; year dummies. Standard errors are clustered by firm. Statistical significance at the ten, five and one-percent level is indicated by *, **, and ***, respectively.

Panel A: Determinants of the Regional Holiday Effect: Univariate Results					
	Epiphany (1988-2009)	Epiphany (2001-2009)	All Saints' Day (1988-2009)	All Saints' Day (2001-2009)	Corpus Christi (2001-2009)
Market Capitalization	0.25*** (10.30)	0.30*** (9.96)	0.19*** (10.93)	0.22*** (11.99)	0.26*** (14.29)
Idiosyncratic Risk	-4.23 (-1.29)	-3.59 (-0.86)	-9.74*** (-3.65)	-9.06*** (-3.09)	-12.97*** (-3.79)
Residual Media Coverage		0.13** (2.11)		0.07* (1.85)	0.07* (1.81)

Panel B: Determinants of the Regional Holiday Effect: Multivariate Results					
	Epiphany (1988-2009)	Epiphany (2001-2009)	All Saints' Day (1988-2009)	All Saints' Day (2001-2009)	Corpus Christi (2001-2009)
Market Capitalization	0.24*** (8.60)	0.30*** (8.88)	0.16*** (8.69)	0.20*** (10.24)	0.23*** (12.92)
Idiosyncratic Risk	-0.71 (-0.20)	-0.56 (-0.54)	-9.06** (-2.33)	-8.62*** (-2.62)	-7.00** (-1.97)
Residual Media Coverage		0.10* (1.88)		0.07* (1.89)	0.05* (1.78)
$Ret_{+,t}$	15.96*** (7.11)	15.27*** (5.44)	12.13*** (4.15)	14.57*** (8.50)	19.08*** (9.75)
$Ret_{-,t}$	17.84*** (7.02)	19.04*** (5.87)	16.11*** (8.07)	16.34*** (8.29)	17.05*** (7.34)
RMRF	0.12* (1.74)	0.16* (1.78)	0.04 (0.92)	0.09 (1.63)	0.13** (2.17)
HML Beta	-0.03 (-0.57)	-0.07 (-1.29)	0.03 (0.62)	0.05 (1.34)	-0.03 (-0.59)
WML Beta	-0.04 (-0.84)	-0.10 (-1.64)	0.03* (1.95)	0.02 (0.38)	-0.04 (-1.17)
Alpha	-0.86 (-0.00)	2.16 (0.09)	-2.89 (-0.25)	-3.80 (-0.27)	17.58 (1.13)
Rural Dummy	-0.16 (-0.95)	0.14 (0.84)	-0.21** (-2.21)	-0.22** (-2.14)	-0.12 (-1.25)
52 Week High Dummy	0.07 (0.62)	0.15 (1.15)	0.20** (2.22)	0.27** (2.32)	0.20** (2.09)
Ad hoc Disclosure (t)		0.28 (0.90)		0.80** (2.47)	0.50* (1.90)
Media Coverage (t+1)		0.32 (1.46)		-0.11 (-1.28)	0.09 (0.88)
Constant	-2.12*** (-8.25)	-3.12*** (-10.31)	-1.58*** (-9.65)	-3.12*** (-10.31)	-3.12*** (-10.31)
Industry and Year Dummies	yes	yes	yes	yes	yes
R^2	0.18	0.26	0.11	0.16	0.17
N	1,997	1,037	3,963	2,422	2,794

Investor characteristics In this section, we aim at gaining additional insights from the daily tracking records of roughly 3,000 retail clients of a German online broker from January 1997 to April 2001. Comprehensive information about the sample, such as details about the construction of portfolio holdings, is given in Glaser and Weber (2009) and Glaser and Weber (2007). Sample investors account for a total of 316,134 stock transactions, out of which 136,125 take place in 965 German firms. As the latter represent roughly 50% of all transactions traceable via Datastream, investors seem to exhibit a strong home bias. Panels A to C of table 2.8 provide descriptive statistics, which show that sample investors trade frequently. The mean (median) number of transactions in German firms is 47 (22), leading to a total sample trading volume of more than 750 million Euro.

For the purpose of our analysis, the data set has two advantages. First, the broker does not offer investment advice. Therefore, trading decisions are not affected by bank recommendations. Second, online broker investor trading on regional holidays is not restricted in any way. Results suggestive of localized trading might thus be considered conservative in the sense that other investors might face higher obstacles, such as finding an open bank office.[17] A disadvantage of the sample is that investor location is not provided. Given this limitation, exploring to what extent investors exhibit local bias (in addition to home bias), is not a straightforward exercise. We thus start our analysis with the reasonable assumption that a disproportionate fraction of the broker's clients live in the region in which the broker is headquartered. Locally biased investors should then have a strong preference for firms also located in the affected metropolitan area.[18] To test this, we compute a sample investor preference measure as the difference between a firm's brokerage weight and its weight in the market portfolio of German stocks. The firm's brokerage weight is defined as the total volume invested in the firm's stock by the broker's clients divided by the total volume the clients invest in all German stocks at the time. We do so at the beginning of each month and for each firm traded at least once on any day by any sample investor. We average stock-specific time-series to obtain an average estimate, based on which we sort firms in one of three portfolios of equal size: "Low preference", "medium preference" and

[17]Note again that this does not have cross-sectional implications for abnormal stock turnover unless local investors' trading decisions systematically deviate from remote investors' buys and sells.

[18]To sharpen the analysis, we focus on the metropolitan area classification as outlined in section 2.4.2. Results are similar when we make use of states instead. Moreover, to mitigate the effect of a few extremely large trades that could materially affect the analysis, we winsorize investor transactions at the 99.9% level in all following tests.

Table 2.8: Online Broker Sample: Descriptive Statistics, Local Bias, and Trading Shocks during Regional Holidays

This table presents results from the analysis of retail investor trading based on daily data. The sample period starts on January 1, 1997 and ends on April 17, 2001. All values are in Euro. Panels A to C provide descriptive statistics. Panel D shows the standardized fraction of firms that are located in the same metropolitan area as the online broker across sample investor preference portfolios. Investor preference for each stock in the online broker sample is defined as the difference between a firm's brokerage weight and its weight in the market portfolio of German stocks, averaged across monthly observations. Each portfolio contains an equal number of stocks. Values reported in panel D are standardized by dividing each fraction by the fraction obtained for the medium preference portfolio. Panels E and F provide results from two separate tests of shocks in trading activity at the day of the holiday, as described in detail in the text.

Panel A: Aggregated Data (1,084 trading days, 2,901 investors, 965 German stocks)							
	No. Transactions	Total Transaction Value	No. Sells	Total Value of Sells	No. Buys	Total Value of Buys	
	136,125	765,300,000	59,770	381,900,000	76,355	383,300,000	
Panel B: Cross-sectional Statistics for Individual Transactions							
		Mean Value	Median Value	SD	1%	99%	
	Transactions: All	5,622	2,733	16,044	128	44,407	
	Transactions: Buys	5,021	2,523	14,676	125	38,059	
	Transaction: Sells	6,390	3,066	17,607	140	50,832	
Panel C: Cross-Sectional Statistics for Individual Investors							
		Mean	Median	SD	1%	99%	
	Number of transactions	47	22	95	1	447	
	Number of firms traded	15	11	16	1	85	
	Value of transactions	263,792	65,743	993,767	580	3,288,099	
Panel D: Standardized Fraction of Firms Located in the Broker Metropolitan Area by Sample Investor Preference Portfolios							
				Low Preference	Medium Preference	High Preference	
				0.98	1	1.29	
Panel E: Percentiles of Relative Trading Activity during the Holiday by Preference Portfolios							
			All Portfolios	Low Preference	Medium Preference	High Preference	
		Value of Transactions	31	61	42	24	
		Number of Transactions	32	49	44	29	
		Number of Active Investors	35	50	43	29	
Panel F: Percentiles of Shock Variable at the Event Day by Firm Size							
Size Group	Epiphany 1997	Epiphany 1998	Epiphany 1999	Epiphany 2000	All Saints' Day 1999	All Saints' Day 2000	Corpus Christi 2000
Size: All	50	75	46	43	28	72	32
Size: Large	50	72	64	56	16	66	44
Size: Small	34	39	25	16	30	5	11

"high preference". Then, for each of these portfolios, we determine the fraction of firms located in the same metropolitan area as the online broker itself. As the metropolitan area turns out to be large, there is sufficient level of diversification. Consequently, if sample investors were not locally biased, we would expect the fraction of firms located near the online broker to be similar across preference portfolios. However, panel D shows that this is not what we find. The fraction of the "medium preference" portfolio is standardized to 1. Therefore, the value 1.29 for the "high preference" portfolio implies that there are close to 30% more local firms than would be expected on average by chance.

Having verified the existence of at least some local bias, we turn to a test suggested by hypothesis 1: Holiday trading activity should decrease in local bias. We label each firm located in the broker's metropolitan area a "low preference", "medium preference" or "high preference" firm. Then, we compute the daily fraction of aggregate sample investor trading volume that is attributable to each of these portfolios, leading to an empirical benchmark distribution for portfolio-specific relative trading activity. Similarly as in previous tests, we determine the percentile of the distribution that is observable during the day of the regional holiday.[19] Hypothesis 1 predicts that these percentiles should decrease in local investors' preference - firms with a high degree of local bias should exhibit a more pronounced shock in relative trading volume. Panel E shows that this is indeed what we find. The "high preference portfolio" temporarily exhibits the lowest trading activity, no matter if one focuses on the total Euro volume traded, the number of transactions conducted or the number of investors trading.

We now turn to hypothesis 3, which posits that the turnover drop in small stocks is disproportionately caused by private investors. To this end, we aggregate data and conduct tests based on shocks in a measure called $Ratio_{i,t}$. For holiday i, it is computed as the overall fraction of daily "holiday firm trading" by online broker investors divided by the fraction of daily "holiday firm trading" by the whole market. The rationale is as follows: As the daily trading volume of the investor sample is positively correlated (0.39) with the daily market trading volume for these firms, it appears justified to use market volume as a benchmark. By focussing on shocks of $Ratio_{i,t}$, one mitigates the problem of lacking information on investor location, as the expected level of trading in each group of stocks

[19]To sharpen the analysis, we focus on the holiday that most clearly separates the broker's metropolitan area as a holiday region from as many other metropolitan areas as possible.

is automatically accounted for. To identify shocks, we control for the autoregressive properties of $Ratio_{i,t}$ by employing AR(p)-processes similar to Connolly and Stivers (2003). Shocks are defined as the residual $\epsilon_{i,t}$ from the following regression:

$$Ratio_{i,t} = \beta_{i,0} + \sum_{k=1}^{p} \beta_{i,k} Ratio_{i,t-k} + \epsilon_{i,t} \tag{2.4}$$

P denotes the maximum lag, up to which each estimated coefficient on each lagged term of $Ratio_{i,t}$ is individually significant, and takes on values between two and five for the specifications described below. $\epsilon_{i,t}$ can thus be interpreted as unexpected daily changes in holiday firm trading of retail investors as compared to the whole market.

To test hypothesis 3, we compute $Ratio_{i,t}$ separately for the whole sample as well as for small and large stocks, split by the median of market capitalization at the beginning of the year. We do this for each of the three holidays. We then determine the most suitable AR(p)-process for each of the nine specifications and run the regression as given in Equation (4). This results in nine shock time series. Finally, we apply these to the seven holiday observations that take place on a trading day during our retail investor sample period: Epiphany is celebrated four times, All Saints' Day twice and Corpus Christi once.

Panel F of table 2.8 reports the percentiles of the shock variables for each stock sample (all, large, small). The results for large stocks and for the whole sample appear like random draws from the distribution. In other words, there are no systematic differences between individual investors and the overall market. However, focussing explicitly on smaller firms, a clear pattern emerges: Online broker investors' trading activity consistently exhibits negative shocks at the day of the holiday when benchmarked against the whole market. The value of the shock variable is well below its median for every single observation. Assuming independence, the likelihood of observing this result by chance is below 1%. In other words, the findings are consistent with hypothesis 3.

2.6 Conclusion

We run a series of natural experiments which collectively suggest that local bias leaves discernible traces in the cross-section of firm-level trading activity. The German setting allows us to compare abnormal turnover in several treatment groups, i.e. hundreds of firms in holiday regions, with turnover in control groups, i.e. in many ways very similar firms in non-holiday regions. Ceteris paribus, firms in holiday regions are remarkably less traded. This finding is mostly confined to the day of the holiday itself, statistically significant, economically meaningful, robust, and does not appear to be completely driven by differences in information release. Instead, consistent with a local bias explanation and the model of Merton (1987), it is particularly strong for firms less recognized by non-local investors. Moreover, in line with predictions of previous research, the turnover shock in smaller stocks seems to be disproportionately caused by individual investors.

The basic message of this study is a simple one: Local investor clienteles are strong and pervasive enough to generate frictions segmenting the stock market along a geographical line. Our analysis also contributes to research on determinants of firm-level trading volume by establishing cross-sectional regularities related to firm location, firm visibility, and investor clienteles. Moreover, by uncovering a link between the potentially powerful role of local investors, investor distraction, and the cross-section of firm turnover, we might provide a new fruitful starting point for the emerging research on the joint dynamics of investor attention, trading volume, and price discovery.

Chapter 3

Losing Sight of the Trees for the Forest? Pairs Trading and Attention Shifts

3.1 Introduction

Relaxing the strict assumptions of traditional models, recent theoretical work argues that investors have limited information processing capabilities. Consequently, they have to optimally allocate their finite attention across several aggregation levels, which is done depending on priority and urgency. As Peng and Xiong (2006) put it: "In severely constrained cases, the investor allocates all attention to market- and sector-level information and ignores all the firm-specific data" (p. 565). In this chapter, we empirically explore asset pricing implications of this attention shift hypothesis. Our objective is to directly test how the dynamics of investor inattention affect the price formation of linked assets.

We create a novel proxy for time-varying investor distraction and explore its role in a natural, promising, and so far widely neglected setting: Pairs trading (Gatev et al. (2006)), a popular relative-value arbitrage approach, which bets on the future performance of two assets with very similar past performance. Relying on close to 50 years of daily data for the US stock market as well as on insights from eight major international markets, we provide broad and robust evidence for distraction effects. For instance, pairs trading is much more profitable than usual when stocks diverge on so called high distraction days, during which turbulent market conditions are assumed to demand investors' full attention. It is much less profitable than usual when stocks diverge on low distraction days, during which we expect sufficient resources to process complex interactions at the firm-level.

Given the vast amount of news available in financial markets, recent models propose and empirical work verifies that investors exhibit category learning behavior[1]: Most effort is typically spent on processing news relevant primarily on some aggregated level, as this information tends to be most important for the valuation of an investor's overall portfolio. The remaining capacities are used to process more disaggregated (e.g. firm-level) news. The dynamics of this setup lend support to the idea that the relative inattention to disaggregated information should be particularly high in exceptional market conditions: The need to focus on understanding shocks in the big picture should leave fewer resources available to concentrate on details. Empirically investigating this prediction first requires answers to two questions: How to proxy for unobservable investor attention allocation? And which return anomaly is likely to be particularly affected by attention shifts?

A few studies so far have dealt with these questions and thereby focussed on explaining variations in the post-earnings announcement drift. We contribute to this literature in two ways: We propose a novel proxy for investor distraction, and we apply it to pairs trading, a conceptually different and untested setup. The proxy aims at quantifying the unexpected daily information load market participants need to process in order to timely assess the overall market situation. Building on the premise that information shocks partly manifest themselves in abnormal returns, we do so by condensing the magnitude and dissemination of unanticipated daily return shocks in a broad range of market segments into a single ratio. We perform yearly decile sorts of the proxy in the baseline analysis, and particularly concentrate on "high distraction days" (decile 10) as opposed to "low distraction days" (decile 1). We then test whether the proxy has predictive power for the profitability of

[1]Theoretical work includes e.g. Barberis and Shleifer (2003), Peng (2005), or Peng and Xiong (2006). On the empirical side, a vivid example for category thinking is given in Cooper et al. (2001): During the internet bubble, firms that simply changed their name to dot.com names, but not their business model, experienced positive abnormal post-announcement returns. Similarly, mutual funds that change their names for cosmetic reasons to appear more like a current hot return style, have been shown to attract positive abnormal inflows without improving their performance (Cooper et al. (2005)). An implication of category learning is excessive return comovement as recently identified in various settings. See e.g. Barberis et al. (2005), Greenwood (2008), or Boyer (2011) on index effects, Green and Hwang (2009) on price effects, or Pirinsky and Wang (2006) on location effects.

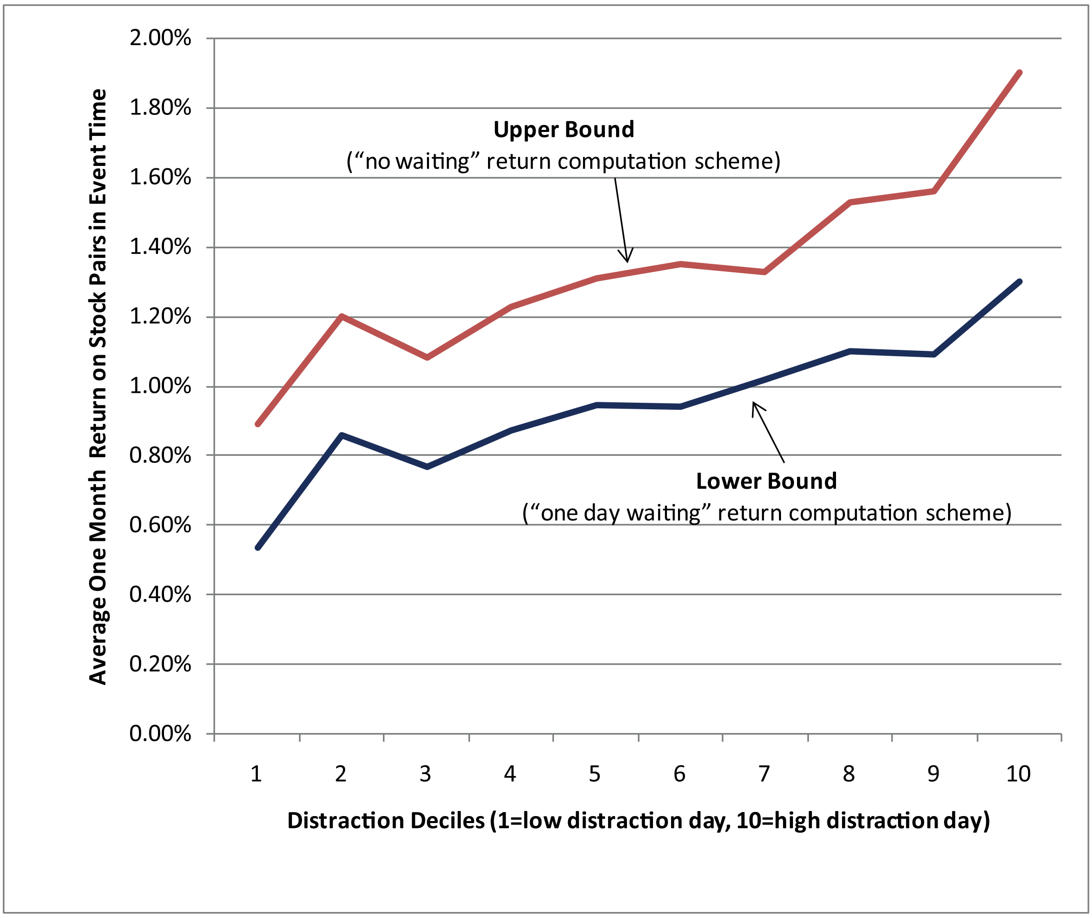
short-term pairs trading, whose mechanisms are illustrated in section 3.2.2. In short, out of the in total 200 million eligible sets of two stocks in our baseline US sample, we find those whose prices have moved together the most historically. Each month, we select the 100 pairs with minimum distance between normalized historical return paths, and then trade them over the adjacent six months. Specifically, whenever the difference in cumulative daily returns of any of these top pairs exceeds a certain threshold, we short the relatively overpriced winner and buy the relatively underpriced loser. If the future resembles the past, prices are likely to finally convergence again, thereby generating positive returns on zero-cost portfolios. We are interested in whether it makes any difference whether stocks diverge on high or low distraction days. Do shocks in limited attention towards firm-level information hinder market participants from keeping relative prices in line?

The essence of our findings is captured in figure 3.1. It displays, in event-time, the average one-month return on long-short US stock pairs by distraction proxy decile ranks. Findings are based on more than 100,000 round-trip trades between January 1962 and December 2008. The lower (upper) line can be interpreted as lower (upper) bound for the return achieved by the strategy (see section 3.2). There appears to be a close to monotonic increase in the profitability by distraction deciles. The return on pairs opening on low (high) distraction days is far lower (higher) than returns on average. The difference between decile 1 and 10 is not only highly statistically, but also economically significant: The return on high distraction days is more than twice as high as the return on low distraction days. This time-varying profitability of pairs trading might also be interpreted in the sense of Grossman and Stiglitz (1980). The distraction proxy is likely to identify moments in which gathering and processing firm-specific information is particularly costly, so that the market has to provide higher payoffs as compensation.

These return differences appear robust. For instance, they are not sensitive to the specific design of the distraction proxy. They are also quite persistent over time, including the recent past, when unconditional pairs trading yields rather low returns. An approach which aims at isolating the distraction effect in calendar time exhibits little exposure to well-known risk premia. Firms tend to be large and liquid, and standard pair characteristics are very similar across distraction deciles. To mitigate concerns that unobserved variables might drive our results, we also examine, with similar results, returns to a subset of pairs that happen to diverge on both high and low distraction days.

Figure 3.1: One Month Return on Pairs by Distraction Proxy Decile Ranks in Event Time

This figure shows the average one month event-time return on US long-short stock pairs sorted by the distraction proxy decile rank on the day of pair divergence. Findings are based on more than 100,000 round-trip trades between January 1962 and December 2008 (see sections 3.2 and 3.3 for details). After divergence, pairs are hold for up to one month. If they do not converge again before this cut-off date, positions are offset. If pairs converge before this cut-off date, the proceeds are hold in cash until the full month has passed. As any cash-flow before the cut-off date is positive by construction, this is a conservative approach. For the upper bound of the return to the strategy, we compute returns on zero-cost portfolios between the day of divergence (closing price) and the day of convergence (closing price). We refer to this scheme as "no waiting". For the lower bound, we employ a more conservative return computation approach as discussed in Gatev et al. (2006). Specifically, we skip one day after the divergence and add one day following the crossing of the prices. We refer to this scheme as "one day waiting".



Moreover, findings are not confined to the US market. The return difference between high and low distraction days is a persistent phenomenon which, with varying degree, is observable in each of the eight major non-US stock markets we additionally study.

To gain deeper insights, we conduct a variety of additional tests whose results appear in line with the idea of the dynamics of investor distraction contributing to pairs trading profitability. Alternative proxies for limited attention, which we derive from the previous literature, often have an incremental effect. Pairs opening immediately before holidays, when investor distraction is likely to be particularly high, tend to be more profitable and to converge more often than pairs on average. The impact of investor distraction appears lower for pairs consisting of firms from the same industry or for pairs consisting of whole value-weighted industries. Finally, pairs particularly neglected (covered) by the media appear more (less) profitable, and exhibit a higher (lower) sensitivity to changes in the level of investor distraction.

Our empirical approach provides a promising setup to gain insights about the impact of time-varying investor inattention on asset pricing for several reasons.

1. Its quantitative nature allows us to identify sets of linked firms for which cross-stock information transfer is likely to be inhibited in moments of high distraction. The monthly top 100 pairs represent only an extremely small fraction of all eligible pairs, and are identified by exhaustive matching in normalized daily price space. In the baseline analysis, we concentrate on firms from different industries. In this way, it provides an intuitive, elegant way of identifying firms, which, despite mainly operating in different segments, are likely to be somehow economically related. Such pairs are interesting candidates for our scenario as industrial boundaries have been shown to along with informational boundaries induced by specialization of important market participants such as analysts or fund managers (e.g. Hong et al. (2007), Menzly and Ozbas (2010)). Moreover, there appears to be substantial information content in residual pairwise stock return comovement, even when an exhaustive list of explaining variables is relied on (e.g. Chen et al. (2010), Chordia et al. (2011)). In sum, the link between two typical firms in our analysis might be thought of as potentially being strong, but simultaneously often also less explicit, obvious, and transparent, and thus prone to being neglected particularly easily.

2. The type of return predictability in pairs trading is different from the type of return predictability that has been linked to limited attention in the literature so far. Previous studies assets have analyzed the lagged price response of stocks to their own past returns (e.g. Hong et al. (2000)), lead-lag effects between portfolios of stocks

(e.g. Hong et al. (2007), Hou (2007)) or return predictability along the supply chain (Cohen and Frazzini (2008), Menzly and Ozbas (2010)). Pairs trading, however, is about predicting the relative short-term performance of two individual, typically rather large stocks with an often non-obvious relationship, out of which neither is the systematic leader. Linking this type of cross-predictability of returns to variations in investor distraction, is, to our knowledge, new.

3. The nature of pairs trading profits fits well with the idea of attention constraints impeding timely information spill-over. It is a short-term strategy, whose profitability tends to almost monotonically decline in event-time (e.g. Engelberg et al. (2009) and section 3.3). Importantly, the day of divergence appears to be a critical date. In fact, a large fraction of the cumulative return difference upon divergence is attributable to the day of divergence itself. Thus, identifying circumstances in which this behavior is ex ante more likely to be caused by temporary market frictions is a key to the strategy's success.

4. In general, comprehensive empirical studies on pairs trading are still rare. This is surprising given its large seemingly abnormal returns reported in Gatev et al. (2006) as well as its apparent popularity among practitioners. Moreover, very little is known about pairs trading in international markets, even though only very few trading strategies have survived the test of time and independent scrutiny. As a consequence, it is still an open question when, where, and why pairs trading is particularly profitable. We address this gap in the literature with a data set comprising about 14,000 stocks with 25 million firm days from eight major non-US stock markets.

5. Our findings might shed light on other pervasive empirical puzzles. A number of scenarios are related to pairs trading in that there also appear primarily short-term price discrepancies between similar assets, which are often difficult to reconcile with standard theory.[2] In a broader sense, our results might thus help to better understand

[2]For instance, Lee et al. (1991), Pontiff (1995), Chay and Trzcinka (1999), and Cherkes et al. (2009) focus on the relationship of the prices of closed-end fund shares and the per share market value of the assets hold by the funds. Lamont and Thaler (2003a) and Mitchell et al. (2002) study situations where a firm's market value is less than the value of its ownership stake in publicly traded subsidiary. Scruggs (2007), Rosenthal and Young (1990), Froot and Dabora (1999), and Jong et al. (2009) study price parity deviations of dual-listed companies ("Siamese Twins"). Gagnon and Karolyi (2010) study discrepancies between the prices of US and home-market shares of companies with cross-listed stocks. Smith and Amoako-Adu (1995), Zingales (1995), and Schultz and Shive (2010) study dual class shares issued by the same company, that differ in voting rights, but have equal cash flow rights.

how limited attention affects the efficiency of related assets in practice.

The remainder of this chaper is organized as follows. Section 3.2 discusses related research and explains our empirical design. Section 3.3 presents baseline findings, both for the US and international markets. Section 3.4 provides a number of robustness checks. Section 3.5 contains further tests that provide additional evidence of the link between time-varying investor inattention and pairs trading profits. Section 3.6 concludes.

3.2 Related Literature and Empirical Design

3.2.1 Limited Investor Attention

Extensive evidence from psychological research shows that attention is a scarce cognitive resource. Focussing attention on one task necessarily goes along with a substitution of cognitive resources from other tasks (Kahneman (1973)). Building on these insights, a growing body of empirical and theoretical work highlights the importance of attention constraints in finance. This research argues that market participants have to be selective in information processing and thus potentially neglect value-relevant information. In the presence of at least some limits to arbitrage, this can induce temporary mispricings.

As investor attention allocation is not observable, the identification of promising proxies is a challenge for empirical work. A substream of this literature defines simple, intuitive time-series proxies for limited investor attention and employs them to explain variations in the magnitude of return anomalies. So far, these papers almost exclusively focus on the post-earnings announcement drift. Hirshleifer et al. (2009) use the number of same day earnings releases. They find that, on days where many earnings announcements compete for investors' attention, average immediate market reactions are weaker, but post-announcement abnormal returns are higher. Qualitatively similar results are reported by DellaVigna and Pollet (2009) and Peress (2008). DellaVigna and Pollet (2009) rely on Fridays, on which, as they argue, investors are distracted by the upcoming weekend. Peress (2008) additionally employs the daily number of firms covered in the Wall Street Journal. Hou et al. (2009) use down market periods, during which investors are assumed to often "put their heads in the sand" (see also Karlsson et al. (2009)). They study, in addition to the post-earnings announcement drift, variations in momentum profits.

We contribute to this literature by providing consistent evidence based on a novel proxy, which relies on the intuition behind models on the dynamics of attention allocation such as Peng (2005) or Peng and Xiong (2006). It aims at identifying days on which market participants are likely to be forced to spend more (or less) resources than usual on understanding "the big picture". Implementing this idea leaves many degrees of freedom. To assure robustness, we first construct a baseline proxy and then, in section 3.4.6, extensively test the sensibility of our findings with ten modified proxies.

For the construction of the baseline proxy, a four-step procedure is employed. First, for January 1960 to December 2008, we compute daily value-weighted returns for the 49 Fama and French (1997) industries[3], thereby taking into account all common shares (CRSP share code 10 or 11) traded on NYSE, AMEX or NASDAQ. Second, we decompose industry returns to construct daily industry-specific return shocks. Specifically, the shock $AR_{i,t}$ for industry i at day t is defined as the absolute difference between the actual industry return $R_{i,t}$ and its expected return as given by a simple OLS market model:

$$AR_{i,t} = \mid R_{i,t} - \widehat{\alpha}_{i,t} - \widehat{\beta}_{i,t} R_{m,t} \mid \tag{3.1}$$

Parameter estimates are obtained from rolling time-series regressions based on daily return data over the previous year. We later augment the model with well-established risk factors. Third, we condense these shocks into a single measure $Distraction_t$. Out of the several plausible weighting schemes, we choose an approach that takes the expected level and frequency of industry-specific shocks into account. Each industry weight $w_{i,t}$ is determined by the inverse of the volatility $\sigma_{i,t}$ of the industry shock variable $AR_{i,t}$ as follows:

$$Distraction_t = \sum_{i=1}^{49} w_{i,t} AR_{i,t} \text{ where } w_{i,t} = \frac{\frac{1}{\sigma_{i,t}}}{\sum_{i=1}^{49} \frac{1}{\sigma_{i,t}}} \tag{3.2}$$

Shock volatilities $\sigma_{i,t}$ are estimated from $AR_{i,t}$ over the previous year. The weighting approach fits with the intuition that a pronounced return shock in an industry for which

[3]Specifically, we use the 48 industries defined in Fama and French (1997), and group stocks that are not assigned to any industry in category 49. In the baseline approach, we focus on this industry classification as markets are partially segmented by industrial boundaries (e.g. Menzly and Ozbas (2010)), as the Fama and French (1997) system appears to identify economically similar companies (e.g. Chan et al. (2007)), as it is widely relied on in academic studies, and as it is available for the whole sample period.

large shocks are a common occurrence is less likely to unexpectedly demand extra attention than a pronounced shock in an industry which “usually behaves as expected”.[4] Figure 3.2 displays the time-series of the resulting raw proxy from January 1962 to December 2008.

An intuitive way of exploring its ability to identify distracting moments is to explore when it reaches its maximum. Indeed, these days are appealing. The highest values (in descending order) are achieved on October 20, 1987 (the day following the stock market crash), on March 15, 2000 (massive sell-off of technology stocks towards traditional industries right before the burst of the bubble), and on September 17, 2001 (first trading day after 9/11).[5] Figure 3.2 also reveals that there are several phases (but no general time trend), in which proxy values typically differ substantially from the sample average.[6]

To thoroughly test for distraction effects despite these episodes, we perform yearly sorts of the proxy as the final fourth step. For each year separately, we assign a decile-based rank to each trading day. Pooling the data results in roughly 1,180 days for each decile rank. Figure 3.2 shows the time-series of the monthly number of high distraction days (decile 10) and low distraction days (decile 1). It also shows Spearman rank order correlation coefficients between distraction proxy decile ranks and the rank order of market-level variables. The proxy is only weakly correlated with standard risk premiums and (moderately) positively with factors each assumed to capture a specific aspect of turbulent markets (squared market return, market turnover, rolling ten day return volatility from t-10 to t-1).

[4] In unreported findings, we find that volatility-weighting often appears a compromise between value-weighting, where few large industries substantially drive the aggregate measure, and equal-weighting, where the impact of small industries is much stronger. Nevertheless, all three weighting schemes result in highly pairwise correlated (0.9 or greater) distraction proxies. All weighting schemes are relied on in later robustness tests in section 3.4.6.

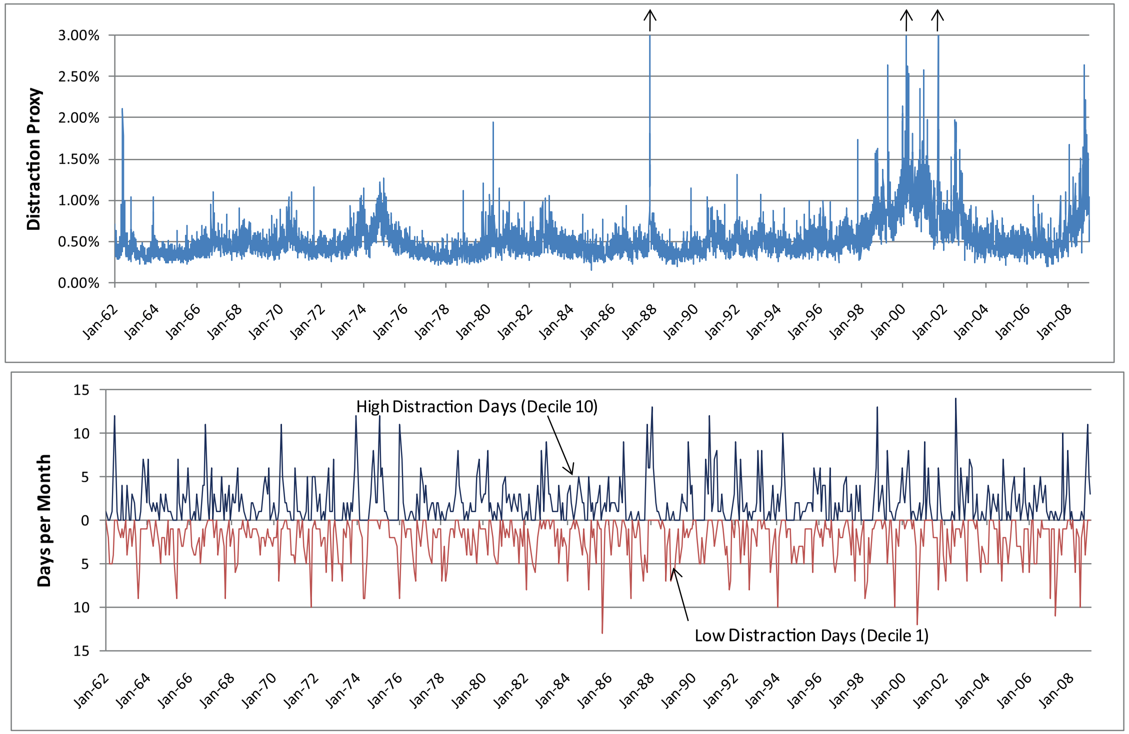
[5] Note that the proxy not simply picks up market movements. The value-weighted market return on these days is 0.40%, 0.68% and -5.07%, respectively.

[6] This appears in line with recent findings on the behavior of idiosyncratic volatility (e.g. Brandt et al. (2010), Fink et al. (2010)).

Figure 3.2: Time Series Characteristics of Investor Distraction Proxy

The upper graph shows the daily development of the raw distraction proxy from January 1962 to December 2008. For its construction, a three-step procedure is employed. First, for January 1960 to December 2008, we compute daily value-weighted returns for the 49 Fama and French (1997) industries. Second, we construct daily return shocks defined as the absolute difference between the actual industry return and its expected return as implied by an OLS market model. Parameter estimates are obtained from rolling time-series regressions based on daily return data over the previous year. Third, shocks are condensed into a single ratio. To this end, industry shocks are weighted by the inverse of the volatility of their shock variable over the previous year. The lower graph shows the monthly number of high and low distraction days based on yearly sorts of the raw distraction proxy in decile ranks. Days with decile rank 10 (1) are referred to as high (low) distraction days. Spearman rank order correlation coefficients between these decile ranks and the rank order of market-level variables based on daily data are as follows. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Market excess return	Small firm factor	Value/growth factor	Momentum factor	Short-term reversal factor	Equal-weighted market return
0.0544***	-0.074***	-0.0231**	-0.1062***	-0.0004	0.0399***
Squared market return	Value-weighted turnover	Equal-weighted turnover	Rolling 10 day volatility	Turnover dispersion	Return dispersion
0.2109***	0.1350***	0.1030***	0.2217***	-0.0848***	-0.0352***



The appendix illustrates the relationship between the distribution of (different types of) abnormal industry returns and distraction proxy deciles ranks. Higher ranks tend to go along both with a generally more pronounced level of abnormal returns and with a higher dispersion of these returns. However, the maximum weight of a single industry-level shock is similar across decile ranks and moreover tends to be moderate. Together, these findings suggest that high distraction days typically identify moments where there is widespread turbulence across markets segments.

3.2.2 Pairs Trading

There are still only few comprehensive empirical studies on pairs trading so far, possibly due to its proprietary and computationally intensive nature. Gatev et al. (2006) report statistically and economically significant profits between 1962 and 2002, which are not driven by standard risk factors, unrealized bankruptcy risk, or short sales constraints. Focussing on same-industry pairs between 1993 and 2006, Engelberg et al. (2009) further explore cross-sectional characteristics of pairs trading. They find that part of the profits to pairs trading seem to stem from differential immediate response to common information, i.e. news that affects both stocks in the pair. Thus, studying dynamics in the level of investor distraction, which might cause such frictions, seems an intuitive way to gain deeper insights. Do and Faff (2010) and Do and Faff (2011) report a declining trend in standard pairs trading profitability over the recent past, which is partly driven by higher fraction of nonconvergent pairs. Again, identifying and understanding scenarios in which pairs are ex ante more likely to converge appears crucial to understand the price formation process. In the international context, Andrade et al. (2005) document annual excess returns of about 10% for the Taiwanese stock market between 1994 and 2002. They show that uninformed trading shocks are a major driver of the strategy's profitability.

For our empirical analysis in the US stock market, we obtain daily stock price data on all common shares (CRSP share code 10 or 11) traded on NYSE or AMEX on any time between January 1960 and December 2008. We impose several restrictions to assure that only relatively large and liquid stocks enter the analysis. We discard all stocks with at least one missing return or zero trading volume on any day of the 12 months estimation period, during which pairs are matched. Moreover, we only consider stocks whose market capitalization is larger than the median of the NYSE/AMEX stock universe at that time. To mitigate data mining concerns and to facilitate comparison with previous work, we widely follow the methodology developed in Gatev et al. (2006).[7] Specifically, at the first day of the 12 months estimation period, we set the price of each eligible stock to equal unity. We use daily price data to compute stock-specific time-series of cumulative total returns (with reinvested dividends) over the whole estimation period. A simple algorithm is then relied on to determine to what extent two stocks, which we require to belong to different (out of the 49) Fama and French (1997) industries, have moved together historically. The algorithm is intended to provide a parsimonious, intuitive framework to identify pairs. Let $R_{i,t}$ ($R_{j,t}$) be the normalized return series of stock i (j) in estimation period t, comprising of trading days 1 to n. The distance measure is then defined as:

$$\frac{1}{n}\sum_{i=1}^{n}(R_{i,t}-R_{j,t})^2 \tag{3.3}$$

We compute this value for all possible pair combinations, whose number grows quadratically with the number of eligible stocks. Then, we choose, at the beginning of each month, the top 100 pairs with minimum distance. These top pairs only represent a tiny fraction (on average less than 0.03%) of all pairs, which aims at identifying strongly linked firms. The 100 pairs are then eligible for trading in the immediately following six months evaluation period. At the beginning of this period, prices are again set to equal unity. If the spread between the cumulative return series of two substitutes exceeds a certain threshold, we go long in the relatively underpriced stock and short in the relatively overpriced stock. Following Gatev et al. (2006), we open a pair if prices diverge by more than two historical standard deviations, as estimated from equation 3. The self-financing pair is then hold for up to one month. If prices convergence before this cut-off date, the trade is closed with a gain. If prices do not convergence within a month, positions are offset, which, if prices diverge even further, results in a loss.[8] A pair may trade several times during the

[7]Note that their setup slightly differs from our baseline scenario in several dimensions. Their sample period is shorter, their eligible stock universe broader, their maximum holding period longer, and their method to identify the top 100 pairs slightly different. In unreported results, we have replicated their main analysis to the extent possible. We obtained findings very similar to theirs. In section 3.4, we assess the sensitivity of our results. They are robust with regard to several plausible changes in methodology (i.e. regarding maximum holding period or top pair identification). Moreover, we provide out-of-sample evidence for in total eight major international stock markets.

[8]A third reason for closing a pair is delisting of a firm. In this case, we use the delisting return or the last available price. Unreported results suggest that the economic impact of this scenario on our findings is weak as the likelihood of delisting within the month after divergence is low. The qualitative nature of our main findings remains unchanged even if we set the return of the long stock to −100% when it is delisted.

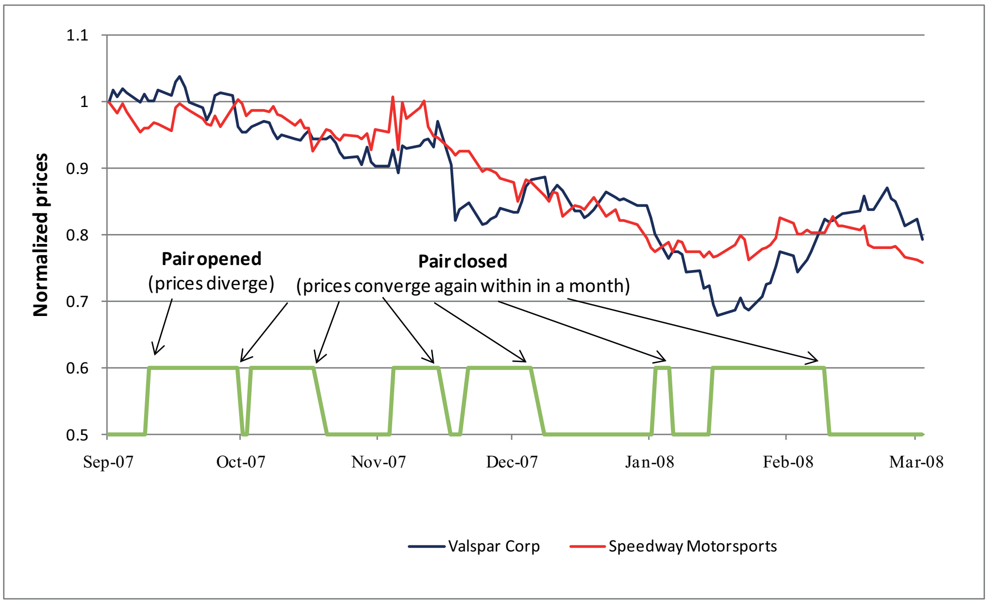
six months evaluation period. The amount of money invested in later trades differs depending on whether we report event-time results (the baseline analysis) or calendar-time results. In event-time, we just again go one dollar long (short) into the cheap (expensive) stock. In calendar-time, proceeds from previous trades are reinvested, which implies that pairs in a portfolio are weighted by the cumulative returns of the component pairs. The bottom-line differences between both methods are small though. We initiate the pairs estimation period at the beginning of every month from January 1960 to July 2007, leading to an evaluation period from January 1961 to December 2008.

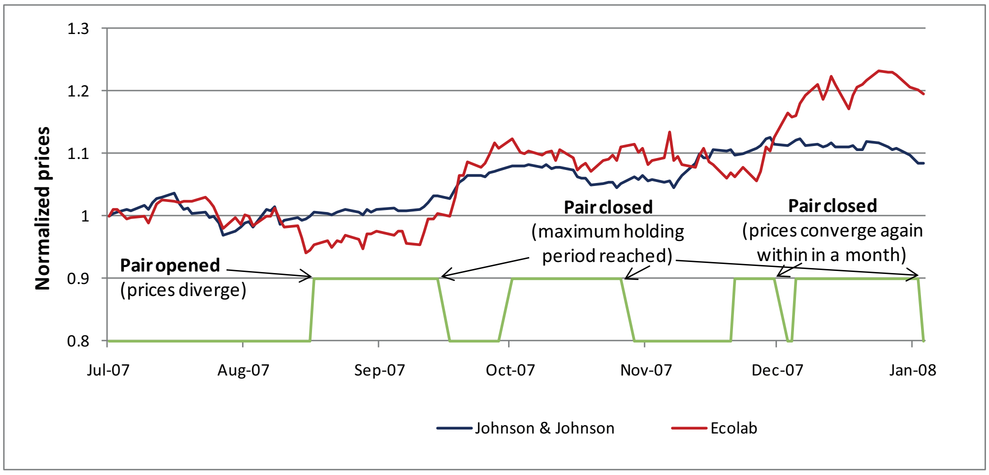
Figure 3.3 illustrates the trading process with examples. Pairs therein open several times during the trading period, however not always in the same direction. This is a common behavior. Out of the large fraction of pairs that open in total at least three times, roughly 85% hold each stock at least once in both a long and a short position. Therefore, the phenomenon is different from the lead-lag relationship studied in earlier work (e.g. Lo and MacKinlay (1990), Hou (2007), Hong et al. (2007)).

Despite the strict screening process as outlined above, microstructural effects might still be an issue. To mitigate these concerns, we report the results from two return computation schemes, that might be considered a lower and upper bound for the magnitude of our findings. For the upper bound, we simply compute returns on zero-cost portfolios between the day of divergence (closing price) and the day of convergence (closing price). For simplicity, we call this scheme "no waiting". For the lower bound, we employ a more conservative return computation approach as discussed in Gatev et al. (2006). Specifically, we skip one day after the divergence and add one day following the crossing of the prices. This method is intended to account for the impact of the bid-ask spread. Moreover, it works strongly against finding effects attributable to investor distraction, as any information overlooked at the day of divergence might be impounded into prices during the next day without entering our return estimates. We call this scheme "one day waiting".

Figure 3.3: Illustration of Pairs Trading Process

This figure illustrates the trading process with two examples. Each month, the 100 pairs with minimum distance between normalized 12 month daily return indices are selected. They are then eligible for trading in the immediately following six months evaluation period. At the beginning of this period, prices are set to equal unity. If the spread between the cumulative return series of the two stocks exceeds two historical standard deviations (as estimated in the estimation period), we go one dollar long in the relatively underpriced stock, which is financed by short-selling the relatively overpriced stock. The self-financing pair is then hold for up to one month. If prices convergence before this cut-off date, the trade is closed with a gain. If prices do not convergence within a month, positions are offset, which, if prices diverge even further, results in a loss. A pair may open several more times during the trading period. In this case, the trading process is repeated as outlined above.





3.3 Baseline Results

3.3.1 US Evidence

We have to ensure that our findings capture the impact of variations in investor inattention rather than variations in other important variables. Therefore, table 3.1 compares firm-level and pair-level variables separately for all trades, for trades opening on low distraction days (decile 1) and for trades opening on high distraction days (decile 10). Inferences are very similar when we also include the remaining deciles in the analysis.

Characteristics related to liquidity and limits to arbitrage are deemed particularly relevant. Our proxies for liquidity comprise market capitalization (NYSE/AMEX decile rank), the Amihud (2002) illiquidity ratio and average pre-event turnover. The latter two are estimated from daily data over the pairs formation period. Besides market capitalization, we employ idiosyncratic risk as a proxy for limits to arbitrage (e.g. Pontiff (2006)). The role of arbitrage constraints will later be analyzed in more detail. Following previous literature, we compute idiosyncratic risk as the volatility of the residual from time-series regressions of daily stock returns on factors for the market premium, size, value and momentum. Again, the twelve months immediately preceding the pair's trading period serve as estimation period. Table 3.1 shows four main findings. First, as aimed at with our selection criteria, firms in general tend to be large and liquid. The medium firm belongs to the ninth NYSE/AMEX decile and has an average daily turnover of 0.11%. Relying on I/B/E/S data from 1980 on (see e.g. Hong et al. (2000)), the medium firm is covered by nine analysts. Second, there are typically only small differences in firm characteristics within pairs and across distraction deciles. The only statistically significant result is found for idiosyncratic risk, where differences seem small from an economic perspective. Third, with regard to industry structure, both firms and pairs are, in the overall picture, well diversified. For instance, both on high and low distraction days, firms from all 49 industry groups and pairs from well more than 600 industry group combinations are traded. However, utility stocks pose an exception. They make up close to 30% of all sample firms and are part of all top industry group combinations. We address this issue in later tests. Fourth, the day of divergence appears an interesting date. Pairs on average are opened when cumulative standardized returns have diverged by 6.68%. More than 40% of this

Table 3.1: Descriptive Statistics for Stock and Pair Characteristics by Distraction Deciles

In panel A, *NYSE/AMEX macap decile* refers to the firm's market capitalization decile rank computed at the beginning of the pair's six month trading period. *Amihud illiquidity ratio* is computed as the average of a stock's absolute daily return divided by its total daily trading volume in million dollars. The estimation period for the illiquidity ratio, for average daily turnover as well as for idiosyncratic risk is the 12 month period ending at the beginning of a pair's trading period. *Idiosyncratic risk* is computed as the standard deviation of the residual obtained from time series regressions of a stock's daily return on factors for the market premium, size, value and momentum. *Maximum industry weight* denotes the largest fraction of sample firms belonging to a specific industry group (out of the 49 Fama/French industries). *Industry concentration* is computed as the sum of squared industry weights. In panel B, the first four rows report within-pair differences of stock characteristics, which are computed as in panel A. The last column reports differences in mean characteristics between decile 10 and decile 1. Standard errors are adjusted for heteroskedasticity and clustered by day of pair divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Variable		All	Distraction Decile 1	Distraction Decile 10	10-1 (Mean)
Panel A: Firm Characteristics by Distraction Deciles					
NYSE/AMEX macap decile	Mean	8.86	8.85	8.86	0.0189
	Median	9	9	9	
Amihud illiquidity ratio	Mean	0.0578	0.0567	0.0566	-0.0002
	Median	0.01	0.0107	0.0094	
Average daily turnover	Mean	0.16%	0.16%	0.17%	0.008%
	Median	0.11%	0.11%	0.11%	
Idiosyncratic risk	Mean	1.12%	1.10%	1.13%	0.032%**
	Median	1.06%	1.05%	1.07%	
No. Analysts (since 1980)	Mean	10.41	10.56	10.21	-0.34
	Median	9	9	9	
No. industry groups		49	49	49	
Maximum industry weight	Fraction	29.14%	29.20%	29.53%	
	Industry	Utilities (across all deciles)			
Industry concentration		0.114	0.115	0.115	
Panel B: Pair Characteristics by Distraction Deciles					
Macap decile difference	Mean	1.25	1.25	1.24	-0.0052
	Median	1	1	1	
Average daily turnover difference	Mean	0.072%	0.072%	0.073%	-0.00%
	Median	0.040%	0.040%	0.039%	
Amihud illiquidity ratio difference	Mean	0.063	0.061	0.061	-0.000
	Median	0.013	0.0130	0.0130	
Idiosyncratic risk difference	Mean	0.248%	0.237%	0.252%	0.015%***
	Median	0.20%	0.19%	0.20%	
Cumulative price difference upon divergence	Mean	6.68%	6.44%	7.04%	0.60%***
	Median	6.28%	6.05%	6.58%	
Return difference at day of divergence	Mean	2.84%	2.38%	3.59%	1.21%***
	Median	2.29%	1.93%	2.89%	
No. industry group combinations		931	623	697	
Maximum industry group weight	Fraction	15.89%	16.04%	15.13%	
	Industries	Utilities/Communication (across all deciles)			
Industry group concentration		0.039	0.041	0.037	
No. round-trip trades		104,125	8,222	14,199	5,977

difference are on average attributable to the day of divergence itself. Thus, understanding what causes prices of related stocks to diverge exactly on these days is critical for the success of any strategy that bets on short-term convergence. On high (low) distraction days, the return spread at the day of divergence is significantly larger (smaller) than on average, which seems consistent with an investor attention story.

We first perform univariate analysis to examine the impact of time-varying investor distraction on pairs trading. To this end, we compare the average event-time return on pairs sorted by distraction proxy decile ranks as observed on the day of pair divergence. Table 3.2 shows findings based on more than 100,000 round trip trades from January 1962 to December 2008. Panel A (B) reports findings under the "no waiting" ("one day waiting") return computation scheme. The first row in both panels reports returns on zero-cost pairs generated within the month following the day of divergence. If pairs converge before this cut-off date, we assume that the proceeds are hold in cash with zero interest rate until the month has passed. As all cash-flows before the cut-off date are positive by construction, this is a conservative approach. In line with previous literature, traditional pairs trading averaged over the whole sample period appears highly profitable. One month returns are estimated between 97 ("one day waiting") and 138 ("no waiting") basis points. When analyzing returns by investor distraction deciles, a clear pattern emerges. Pairs opening on low distraction days are far less profitable, both from a statistical and an economic point of view, than pairs on average. The one month return ranges only from 53 ("one day waiting") to 89 ("no waiting") basis points. On the other hand, pairs opening on high distraction days are far more profitable than pairs on average. Estimates range here from 130 to 190 basis points. The difference between decile 10 and decile 1 amounts to highly significant and economically meaningful 77 to 101 basis points per month. The effect is not confined to the extreme distraction deciles: Decile 2 to 9 show an almost monotonic increase in profitability. The appendix provides more detailed information about the return distribution by distraction deciles.

To gain more insights, we study the mechanisms behind these return differences. In general, higher returns on pairs opening on specific days can stem from three sources: First and foremost, the probability of convergence can be higher. This is indeed what a limited attention story would predict for high distraction days. As implied by e.g. the model of Peng and Xiong (2006), we expect, all else equal, cross-stock information to diffuse more

Table 3.2: One-month Pairs Trading Returns by Distraction Deciles

This table reports event-time one-month returns on zero-cost portfolios of US stock pairs sorted by distraction proxy decile ranks as observed on the day of divergence. Breakpoints for the deciles are determined separately for each year. Calculations are based on daily data from January 1962 to December 2008. In Panel A (B), trading positions in each pair are initiated on the day of divergence (on the day following the convergence) and liquidated on the day of convergence (on the day following the convergence). *Fraction of convergence* refers to the percentage of pairs that converge within the month following the divergence. *Return if convergence* (*Return if no convergence*) refers to the average return generated, thereby conditioning on pairs that do (do not) converge within the month following divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

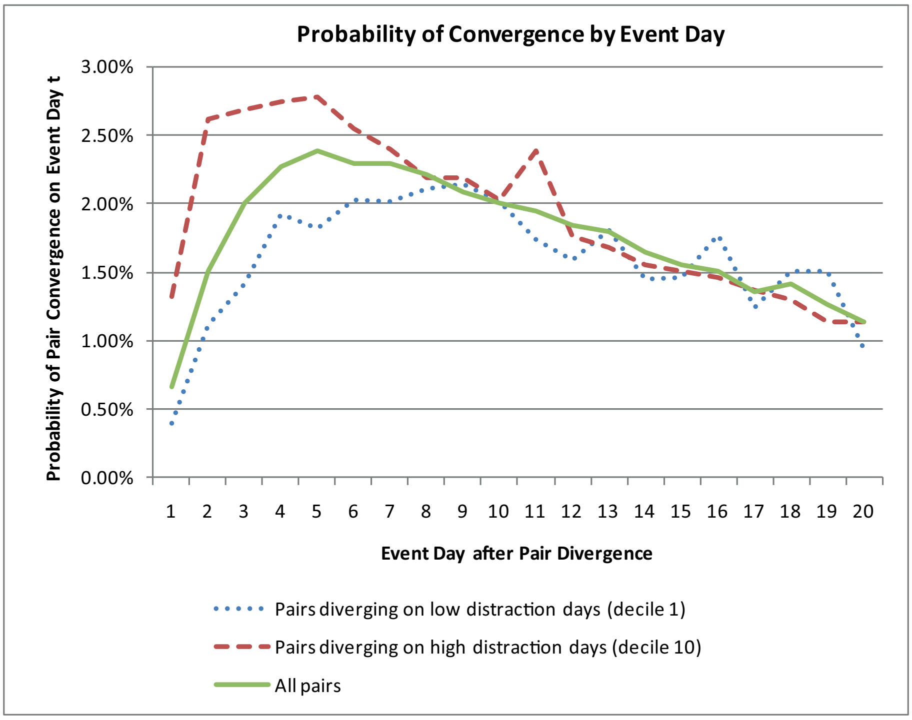
Distraction Decile	All	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: One Day Waiting, Full Sample Period (1962-2008)												
Return on pairs	0.00973***	0.00534***	0.00859***	0.00770***	0.00873***	0.00946***	0.00943***	0.0102***	0.0110***	0.0109***	0.0130***	**0.0077*** **
	(0.000319)	(0.00103)	(0.000956)	(0.000976)	(0.000988)	(0.00100)	(0.00104)	(0.00106)	(0.000917)	(0.000971)	(0.000990)	**(0.00143)**
% of convergence	0.363	0.334	0.343	0.343	0.347	0.362	0.361	0.358	0.376	0.381	0.397	**0.0630*** **
Return if	0.0642***	0.0614***	0.0629***	0.0633***	0.0624***	0.0633***	0.0637***	0.0653***	0.0639***	0.0651***	0.0671***	**0.0056*** **
convergence	(0.000296)	(0.00101)	(0.000874)	(0.000869)	(0.000920)	(0.00103)	(0.000908)	(0.000910)	(0.000851)	(0.000893)	(0.000909)	**(0.00136)**
Return if	-0.0208***	-0.0224***	-0.0194***	-0.0211***	-0.0195***	-0.0208***	-0.0209***	-0.0201***	-0.0202***	-0.0217***	-0.0213***	**0.00112**
no convergence	(0.000343)	(0.000984)	(0.00102)	(0.00106)	(0.00108)	(0.00102)	(0.00115)	(0.00113)	(0.000978)	(0.00108)	(0.00114)	**(0.0015)**
No. of trades	103,386	8,187	8,679	9,146	9,398	10,048	10,079	10,595	11,019	12,224	14,011	**5,824**
Panel B: No Waiting, Full Sample Period (1962-2008)												
Return on pairs	0.0138***	0.00889***	0.0120***	0.0108***	0.0123***	0.0131***	0.0135***	0.0133***	0.0153***	0.0156***	0.0190***	**0.0101*** **
	(0.000341)	(0.00108)	(0.000986)	(0.00103)	(0.00105)	(0.00103)	(0.00106)	(0.00117)	(0.00103)	(0.00104)	(0.00106)	**(0.00151)**
% of convergence	0.363***	0.334	0.343	0.343	0.347	0.362	0.361	0.358	0.376	0.381	0.397	**0.0630*** **
Return if	0.0756***	0.0713***	0.0725***	0.0729***	0.0739***	0.0742***	0.0744***	0.0757***	0.0755***	0.0774***	0.0819***	**0.0106*** **
convergence	(0.000253)	(0.000735)	(0.000636)	(0.000678)	(0.000723)	(0.000775)	(0.000669)	(0.000707)	(0.000664)	(0.000726)	(0.000937)	**(0.00119)**
Return if	-0.0214***	-0.0223***	-0.0195***	-0.0215***	-0.0204***	-0.0216***	-0.0209***	-0.0216***	-0.0210***	-0.0225***	-0.0223***	**0.0001**
no convergence	(0.000351)	(0.00103)	(0.00105)	(0.00109)	(0.00112)	(0.00105)	(0.00118)	(0.00124)	(0.000964)	(0.00110)	(0.00112)	**(0.00152)**
No. of trades	104,125	8,222	8,738	9,179	9,436	10,094	10,122	10,657	11,146	12,332	14,199	**5,977**

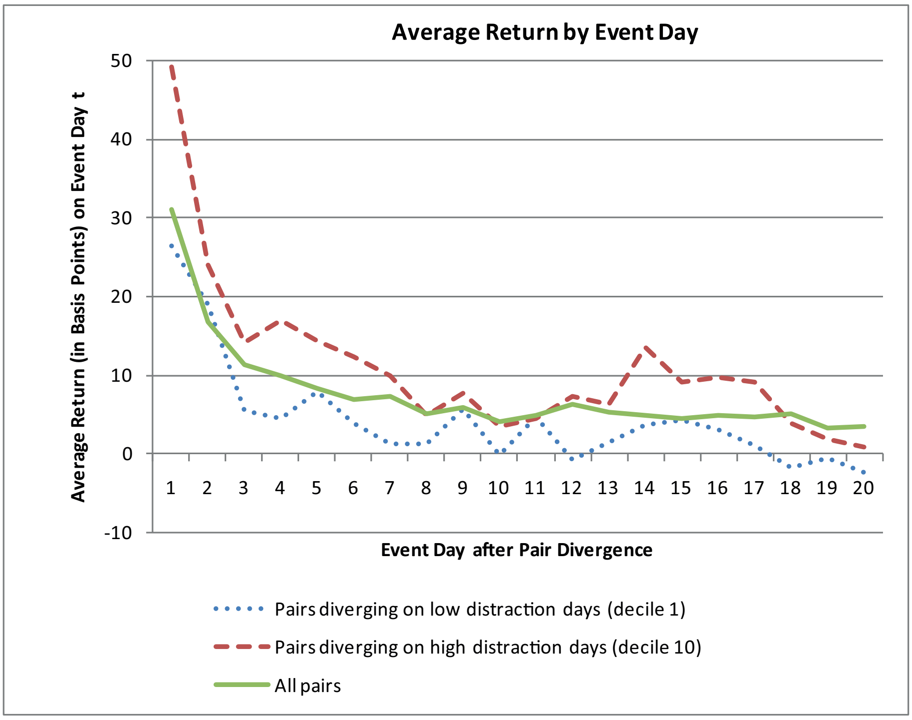
slowly during these times. Imagine, for instance that common news is released, which clearly and directly affects the first firm in the pair, but only indirectly and less clearly the second firm. Market frictions due to high investor distraction are then likely to prevent the news from being instantaneously and fully impounded into the price of the second stock. This might induce temporary price divergence and thus the opening of the pair. Consistent with this line of reasoning, far more pairs open on high distraction than low distraction days (see table 3.2). When investors finally become fully aware of the link between both firms, relative prices should adjust gradually and the pair is likely to finally converge again. The second row of panel A and B shows that this prediction is supported by the data. The average fraction of pairs converging within the month after divergence is 36.3%. For pairs opening on low distraction days, however, the convergence rate is only 33.4%. This value almost monotonically increases by distraction deciles, culminating in a convergence rate of 39.7% for decile 10. In other words, simply switching from low distraction to high distraction days increases the likelihood of convergence by almost 20 percent. Figure 3.4 shows the probability of convergence on a given day in event time. In line with the idea of time-varying investor distraction being an important driver of divergence, the likelihood of convergence within the first event days is considerably higher (lower) for pairs diverging on high (low) distraction days. After about five days, convergence rates begin to approximate each other more closely, until they appear indistinguishable.

Higher returns might also stem from average returns conditioned on convergence being higher. Arguably, this is also what a limited attention explanation of our findings would suggest. To the extent that a slower cross-stock information flow on high distraction days translates ceteris paribus into a higher cumulative return difference at the time of divergence, we would expect to finally gain higher returns upon convergence. Table 3.2 shows findings supporting this line of reasoning. The difference in returns upon convergence between decile 10 and decile 1 is estimated to range between 56 ("one day waiting") and 106 ("no waiting") basis points. In other words, and as also shown in table 3.2, simply switching from low distraction to high distraction days appears to increase the average return upon convergence by roughly 10%. Again, figure 3.4 provides graphical evidence. It also shows that average daily returns almost monotonically decline in event-time, in particular for pairs opening on high distraction days. This again highlights the important role of the day of divergence.

Figure 3.4: Probability of Convergence and Average Daily Return by Event Day

The upper graph shows the empirical probability of US stock pairs converging on a given event day after divergence. See section 3.2.2 for a definition of divergence and convergence. The lower graph shows the average daily return of open pairs in event-time. Both figures are based on more than 100,000 round-trip trades between January 1962 and December 2008 (see sections 3.2 and 3.3 for details).





Finally, a third potential source of profit is that the average return conditioned on non-convergence could be less negative for pairs opening on high distraction days. A limited attention story does not imply that this should be the case: Non-convergence is (comparatively more) suggestive of idiosyncratic news affecting only one stock in the pair (e.g. Engelberg et al. (2009)). As this type of information is arguably often easier to grasp and process than common news affecting the potentially complex relationship between both firms in the pair, attention constraints should be less binding. Again, table 3.2 displays findings consistent with this line of reasoning. The difference in returns upon non-convergence between decile 10 and decile 1 is virtually zero and statistically insignificant. In fact, the returns for this scenario are similar across all distraction deciles.

Taken together, findings are in line with the implications of investor distraction. Pairs opening on high distraction days are more attractive for two reasons: They are more likely to convergence, and, if they do, they generate higher abnormal returns.

To control for other factors that might partially drive our findings so far, we conduct several multivariate tests. Main results are presented in table 3.3. The dependent variable is the pooled one-month event-time return on long-short pairs. For brevity, we only report the more conservative results from the "one day waiting" return computation scheme. The independent variable of interest is the investor distraction proxy. In different specifications, we employ either the distraction proxy decile rank or a high/low distraction dummy, which is zero for low distraction days (decile 1) and one for high distraction days (decile 10). The remaining independent variables comprise up to three control sets. The first set controls for calendar and industry effects (indicator variables for year, month, day of week as well as pair industry group combinations). The second set controls for market-level conditions on the day of divergence (market return, squared market return, market turnover, 10 day rolling volatility, factors for daily return premia on size, value, momentum and short-term reversal). The third set includes almost all pair and firm characteristics outlined at the beginning of this section (see table 3.3 for details).

Depending on the model specification, the difference in one month abnormal returns between pairs opening on high distraction days and those opening on low distraction days is estimated to range from 39 to 73 basis points in the multivariate case. Coefficients remain all strongly statistically significant at the one percent level.

Table 3.3: Multivariate Analysis: Investor Distraction and Returns on Pairs Trading

This table displays findings from pooled multivariate regressions of the one-month return on zero-cost US stock pairs on a proxy for investor distraction and up to three sets of control variables. The proxy for investor distraction is the *Distraction Proxy Decile Rank* (specifications 1-4) or a *High/Low Distraction Dummy* (specifications 5-8), which is zero for low distraction days (decile 1) and one for high distraction days (decile 10). Pairs trading returns are computed under the conservative "one day waiting" return scheme. The first set of explaining variables controls for calendar and industry effects (indicator variables for year, month, day of week, and pair industry group combinations). The second set controls for market-level conditions on the day of divergence (market return, squared market return, market turnover, 10 day rolling volatility, factors for daily return premia on size, value, momentum and short-term reversal). The third set controls for a number of pair characteristics computed as outlined in table 3.1 (average firm market capitalization decile rank, ln (average pre-event turnover), ln (average pre-event Amihud illiquidity ratio), average idiosyncratic risk, within-pair differences in these variables, return difference attributable to the day of divergence, ln (average turnover on day of divergence) and ln (difference in turnover on day of divergence)). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

Model specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample period	1/1962-12/2008	1/1962-12/2008	7/1963-12/2008	7/1963-12/2008	1/1962-12/2008	1/1962-12/2008	7/1963-12/2008	7/1963-12/2008
Observations	103,386	103,386	100,426	99,673	22,198	22,198	21,579	21,281
Adjusted R^2	0.08%	2.62%	2.74%	2.83%	0.30%	5.33%	5.58%	5.74%
Distraction Proxy Decile Rank	0.00065***	0.00065***	0.00040***	0.00039***				
	(0.0001099)	(0.0001049)	(0.0001172)	(0.0001183)				
High/Low Distraction Dummy					0.00770***	0.00734***	0.00542***	0.00557***
					(0.0014263)	(0.0014141)	(0.0017108)	(0.0017519)
Controls for calendar and industry effects	no	yes	yes	yes	no	yes	yes	yes
Controls for market-level conditions	no	no	yes	yes	no	no	yes	yes
Controls for pair characteristics	no	no	no	yes	no	no	no	yes

3.3.2 International Evidence

A powerful way to test the validity of our baseline findings is to evaluate the success of the approach in independent samples. This is particular appealing as, up till now, hardly anything is known about the nature of pairs trading profits in other major international stock markets. Finding similar return patterns across countries would strongly suggest that our findings represent a generalized phenomenon rather than are attributable to US-specific factors or elaborate data mining. Therefore, we study the dynamics of pairs trading profits in eight countries. This number is somewhat arbitrarily set and meant to be a compromise between maximizing the sample size and minimizing the fraction of error-prone daily return and volume data as well as the number of months with too few eligible stocks for a reasonable analysis. Given this trade-off, we rely on Japan, UK, France, Germany, Switzerland, Italy, Netherlands, and Hongkong. These markets represent the eight largest non North-American stock markets based on domestic stock market capitalization at the end of 2002, as reported by Datastream. This date roughly represents the middle of the sample period for most of these countries, for which we gather data from the Compustat Global Daily Stock File. Depending on the availability of reliable trading volume data, the sample period starts at some point in the middle of the 90ies and ends, for all markets, in December 2009. The appendix gives more detailed information about the samples. In total, the analysis is based on an initial data set of about 14,000 stocks accounting for 25 million firm days. The computation of the country-specific distraction proxy relies on the 10 GICS industry sectors. For the country-specific monthly top 100 pairs, we discard all stocks with at least one missing return or at least two zero/missing trading volume days within the 12 months estimation period. Apart from that, the analysis closely mirrors the US approach in table 3.2. Main findings from in total about 200,000 round-trip trades are displayed in table 3.4.

Findings reveal that traditional pairs trading appears in general highly profitable in all countries. This may seem surprising given the fact that we focus on the recent past in which returns on pairs trading in the US have been far smaller than in earlier periods. However, even under the conservative "one day waiting" scheme, annualized returns range from 6% (Italy) to more than 13% (Germany, France). While these results are interesting in their own right, we again focus on the role of investor distraction at the day of divergence. We find strong evidence for distraction effects. With the exception of Japan, the

Table 3.4: Pairs Trading by Distraction Deciles: International Evidence

This table reports profits from pairs trading in international stock markets. The methodology is the same as in the baseline analysis for the US market (see table 3.2). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

	Japan	UK	France	Germany	Switzerland	Italy	Netherlands	Hongkong
	Panel A: One Day Waiting, Full Sample Period (1962-2008)							
Time Period	1/1995-12/2009	1/1995-12/2009	1/1996-12/2009	1/1996-12/2009	6/1997-12/2009	6/1995-12/2009	1/1995-12/2009	1/1995-12/2009
Observations	36,992	27,185	25,833	26,006	16,841	25,596	21,320	20,894
	Panel A: One-month Pairs Trading Abnormal Returns, One Day Waiting							
Pairs Trading Returns: All	0.0103***	0.0073***	0.0111***	0.0109***	0.0054***	0.0048***	0.0082***	0.0100***
	(0.000605)	(0.000762)	(0.000852)	(0.00105)	(0.00130)	(0.00117)	(0.00111)	(0.00223)
Pairs Trading Returns: Decile 1	0.0119***	0.00278	0.0079***	0.0061*	-0.0065	0.0032	0.0037	-0.0099
	(0.00171)	(0.00200)	(0.00270)	(0.00331)	(0.00427)	(0.00350)	(0.00313)	(0.00679)
Pairs Trading Returns: Decile 10	0.0138***	0.0142***	0.0173***	0.0204***	0.0171***	0.0066	0.0203***	0.0263***
	(0.00197)	(0.00245)	(0.00273)	(0.00324)	(0.00510)	(0.00459)	(0.00342)	(0.00601)
Diff 10-1	**0.0019**	**0.0114*** **	**0.0094** **	**0.0143*** **	**0.0237*** **	**0.0034**	**0.0166*** **	**0.0362*** **
	(0.00260)	**(0.00316)**	**(0.00383)**	**(0.00463)**	**(0.00664)**	**(0.00577)**	**(0.00463)**	**(0.00906)**
	Panel B: One-month Pairs Trading Abnormal Returns, No Waiting							
Pairs Trading Returns: All	0.0207***	0.0095***	0.0160***	0.0168***	0.0087***	0.0077***	0.0154***	0.0145***
	(0.000685)	(0.000839)	(0.000888)	(0.00111)	(0.00135)	(0.00124)	(0.00125)	(0.00214)
Pairs Trading Returns: Decile 1	0.0216***	0.0033	0.0111***	0.0096***	-0.0035	0.0056	0.0103***	-0.0076
	(0.00189)	(0.00220)	(0.000852)	(0.00331)	(0.00434)	(0.00359)	(0.00373)	(0.00676)
Pairs Trading Returns: Decile 10	0.0270***	0.0197***	0.0227***	0.0301***	0.0219***	0.0117**	0.0315***	0.0334***
	(0.00209)	(0.00259)	(0.00279)	(0.00345)	(0.00520)	(0.00491)	(0.00386)	(0.00561)
Diff 10-1	**0.0055***	**0.0164*** **	**0.0105*** **	**0.0204*** **	**0.0253*** **	**0.0062**	**0.0212*** **	**0.0409*** **
	(0.00282)	**(0.00340)**	**(0.00398)**	**(0.00477)**	**(0.00677)**	**(0.00608)**	**(0.00536)**	**(0.00878)**
	Panel C: Fraction of Convergence							
% of Convergence: All	0.448***	0.289***	0.296***	0.296***	0.195***	0.267***	0.232***	0.231***
	(0.00423)	(0.00455)	(0.00411)	(0.00430)	(0.00473)	(0.00417)	(0.00536)	(0.00549)
% of Convergence: Decile 1	0.438***	0.256***	0.269***	0.270***	0.148***	0.250***	0.209***	0.159***
	(0.0127)	(0.0139)	(0.0144)	(0.0132)	(0.0137)	(0.0140)	(0.0178)	(0.0128)
% of Convergence: Decile 10	0.491***	0.341***	0.328***	0.322***	0.244***	0.300***	0.301***	0.298***
	(0.0127)	(0.0147)	(0.0116)	(0.0147)	(0.0160)	(0.0132)	(0.0178)	(0.0160)
Diff 10-1	**0.0537*** **	**0.0850*** **	**0.0589*** **	**0.0514*** **	**0.0965*** **	**0.0500*** **	**0.0920*** **	**0.139*** **
	(0.0179)	**(0.0202)**	**(0.0185)**	**(0.0197)**	**(0.0211)**	**(0.0192)**	**(0.0252)**	**(0.0205)**

return on pairs opening on low (high) distraction days is smaller (larger) than average sample returns in every singly country. The positive return difference between decile 10 and decile 1 is, with the exception of Italy and Japan, persistently and strongly statistically significant. In addition, their size is economically meaningful and sometimes even very large. Moreover, the nature of pairs trading profits in Japan does not seem to be that different. Focussing on distraction quintiles instead of deciles yields findings which become more in line, both statistically and economically, with the ones obtained for the other countries. Digging deeper, panel C of table 3.4 reveals that the key to the pronounced profits on high distraction days is again a higher likelihood of convergence. From low distraction days to high distraction days, the fraction of converging pairs increases between 12% (from 43.8% to 49.1% in Japan) to 87% (from 15.9% to 29.8% in Hongkong). Remarkably, while self-financing pairs trading generates seemingly abnormal returns in all countries, its nature appears to differ substantially e.g. with regard to the number of pairs traded, the impact of the "one day waiting" scheme, or the (unconditional) fraction of converging pairs. Exploring the sources and consequences of these cross-sectional differences might be an interesting field for further research. In any case, the results in the overall picture strongly confirm the baseline results obtained for the US market.

3.4 Robustness Checks

In this section, we test the sensitivity of our baseline findings from various perspectives. For the sake of brevity and if not mentioned otherwise, we only report results obtained under the more conservative "one day waiting" scheme.

3.4.1 Subperiod Analysis

To assess whether our findings are robust across time, we repeat the analysis for three consecutive subperiods of (close to) equal length. Panel A of table 3.5 shows findings for the periods from 1962 to 1977, from 1978 to 1993, and from 1994 to 2008.

In line with results from previous work (Gatev et al. (2006), Do and Faff (2010)), returns to traditional pairs trading seem to decline over time, though they remain statistically significant. For the most recent subperiod, the one-month return is only 24 basis points,

Table 3.5: Robustness Checks

This table presents results from various robustness checks. For brevity, we only report results obtained under the more conservative "one day waiting" return computation scheme. Panel A displays subperiod results from the baseline approach. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. In Panel B, the way the monthly top 100 pairs are identified is modified. *Excluding utility firms* means we do not consider any pair with at least one firm belonging to Fama/French (1997) industry group 31. *Only different firms* means we do not select a pair if at least one the firms is already a component of any higher-ranked pair. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. Panel C reports results from Fama-MacBeth-type regressions. We first estimate yearly pooled cross-sectional regressions of one-month pairs returns on distraction decile ranks and then use the time-series of resulting coefficients to assess the statistical significance of the distraction proxy. Newey-West-adjusted standard errors are reported in parentheses. Panel D shows results for *same pairs*, i.e. a subsample of pairs that diverge both at least once on a high distraction day and on a low distraction days. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Distraction Decile: All	Distraction Decile: 1	Distraction Decile: 10	Difference: 10-1
Panel A: Subperiod Analysis				
Subperiod: 1962-1977	0.0149***	0.0104***	0.0177***	**0.0073*** **
	(0.000511)	(0.00173)	(0.00153)	**(0.00231)**
Subperiod: 1978-1993	0.0109***	0.00706***	0.0129***	**0.0059** **
	(0.000528)	(0.00175)	(0.00171)	**(0.00245)**
Subperiod: 1994-2008	0.0024***	-0.0025	0.0079***	**0.0104*** **
	(0.000598)	(0.00174)	(0.00187)	**(0.00255)**
Panel B: Variations in the Data Set (Monthly Top 100 Pairs)				
Excluding utility firms	0.01019***	0.00588***	0.01347***	**0.0076*** **
	(0.00031)	(0.00102)	(0.00097)	**(0.00102)**
Only different firms	0.01080***	0.00785***	0.01435***	**0.0065*** **
	(0.00029)	(0.00091)	(0.00087)	**(0.0013)**
Panel C: Alternative Regression Approach				
Coefficient on distraction decile rank	0.00057***			
	(0.0001509)			
Panel D: Limitation to Firms that Diverge both at Least Once on High and Low Distraction Days				
Same pairs	0.0202***	0.0140***	0.0213***	**0.0073*** **
	(0.000611)	(0.00178)	(0.00160)	**(0.00239)**

possibly as a result of the increasing popularity of such strategies as well as decreasing transaction costs. More importantly though, in all cases, returns originating from divergence on high (low) distraction days are higher (lower) than on average. In fact, between 1994 and 2008, returns on pairs opening on low distraction days are even negative. Nevertheless, for high distraction days, the average return in the same period is 78 basis points, which is three times larger than the return obtained from unconditional pairs trading. The difference between decile 10 and decile 1 is highly significant in all subperiods, both economically and statistically. In sum, our results appear robust across time.

3.4.2 Variations in the Data Set

As shown in table 3.1, firms from the utility sector represent about 30% of all firm-level observations. To analyze whether our findings represent a widespread phenomenon, we control for the impact of utility firms in two ways. In the first scenario, we simply exclude these stocks. We rerun the selection process and the baseline analysis, but only consider pairs that do not include any utility firm. In the second scenario, we identify the monthly top 100 pairs under the constraint that each firm is only considered once at maximum. This approach not only decreases the fraction of utility stocks to roughly 17%, but also changes the composition of the data set considerably.[9] Panel B of table 3.5 verifies, however, that the baseline findings are robust to such variations in the eligible pairs universe.

3.4.3 Alternative Econometric Approach

We also modify our empirical design by running Fama-MacBeth-type regressions. We first estimate yearly pooled cross-sectional regressions of one-month pairs returns on distraction proxy decile ranks and then use the time-series of the resulting coefficient to assess its statistical significance. Panel C of table 3.5 shows the result. The coefficient is positive in about 75% of all years, highly statistical significant, and economically meaningful.

[9] Again, we rank pairs by minimum distance of firms' normalized return series. However, we skip a pair if at least one of the firms is already a component of any higher-ranked pair. As a result, the top 100 pairs always consist of 200 different firms. The rank of the last selected pair is always 100 in the baseline scenario, but on average 782 in the new scenario.

3.4.4 Same Pairs

Though descriptive statistics and multivariate tests suggest that firm and pair characteristics are widely comparable across distraction deciles, the analysis could potentially still suffer from an omitted variables problem. To mitigate these concerns, we analyze a subsample specifically designed to isolate the impact of variations in investor distraction. We restrict our focus to those pairs which happen to diverge both at least once on a low and at least once on a high distraction day. Implementing this idea requires to impose a restriction on the maximum time span between these events. We here report results for the subset of pairs, for which the time difference between the average date the divergence on low distraction days took place and the average date the divergence on high distraction days took place, is less than a year.[10] In total, this leaves 5,488 trades on high or low distraction days. This procedure controls for all firm and pair-level variables, including unobserved ones, that do not vary within this typically rather short time period. Findings are shown in panel D of table 3.5. Results verify that inferences from our baseline findings carry over.

3.4.5 Implementability

The distraction proxy is constructed from yearly decile sorts. This implies that the information it contains is not fully available in real time to market participants, in particular in the first months of a given year. To assure that a trading strategy based on our findings would actually have been implementable, we have modified the proxy construction by relying on rolling historical values. Specifically, the sorting into deciles for a given day is now based on the raw proxy values over the immediately preceding 250 trading days. Put differently, all required information would have been easily at hand in real time. The appendix provides a transition matrix between the baseline proxy and its modification. In the final pairs trading sample, both variables are highly positively correlated (0.87). And indeed, as the appendix shows, findings broadly carry over. Univariate results are only slightly weaker and multivariate results even slightly stronger than in the baseline case.

[10]Results are not sensitive to this specific choice. We have experimented with modifications, such as omitting the one year restriction or such as only considering the first trade in each six months trading period.

3.4.6 Modified Distraction Proxies

Our results might partly be driven by the specific design of our distraction proxy. To address potential data mining concerns, we repeat our baseline analysis with ten alternative proxies, which modify the original approach in many dimensions. Specifically, these proxies differ with respect to the type and number of market segments used (49 industries, 100 portfolios sorted on book-to-market and size, 25 portfolios sorted on size and short-term reversal), with respect to the weighting scheme of return shocks (volatility weighting, equal weighting, value weighting, interquartile range), with respect to the model of expected return (market model, four factor model), and with respect to the type of returns used (abnormal returns, raw returns as in Stivers and Sun (2010)). Table 3.6 gives more information about these proxies and also shows returns by distraction deciles.

Table 3.6 provides a pervasive picture. The difference between decile 10 and decile 1 is statistically highly significant in all cases. Moreover, it keeps its strong economic importance. Finally, results are not confined to the extreme deciles. Instead, in many cases, there seems to be a close to monotone relationship between distraction deciles and returns.

3.4.7 Limits to Arbitrage

In unreported results, we find that only few of the market-level and pair-level control variables in the multivariate analysis are persistently statistically significant. The strongest effect (t-statistic 4.48 in model 4 and 2.60 in model 8 in table 3.3), however, is found for average idiosyncratic risk, supporting the notion that pairs consisting of difficult to arbitrage firms generate larger returns on average. This cross-sectional finding appears in line with insights from related literature (e.g. Gagnon and Karolyi (2010), Engelberg et al. (2009))). It further raises the question whether similar forces are at work in the time-series and whether these might reduce the importance of our distraction proxy. As a proxy for arbitrage risk in the time-series, we rely on the Chicago Board Options Exchange Market Volatility Index (VIX). The VIX a popular measure of the volatility implied in S&P 500 index options and widely considered a forward-looking measure of overall market uncertainty.[11] Several theories suggest that the anticipation of fundamental shocks might

[11] The VIX is not included in the baseline analysis, as daily data is only available on a daily basis from 1990 on. In the time-series, the correlation of our distraction proxy and the raw VIX (yearly decile ranks of the VIX) is 0.22 (0.31).

Table 3.6: Alternative Distraction Proxies: One-month Pairs Trading Returns by Distraction Deciles

This table reports one-month event-time returns on zero-cost portfolios of stock pairs sorted by distraction proxy deciles as observed on the day of the divergence. Breakpoints for the distraction deciles of each proxy are determined separately for each year. In Panel A, factor loadings with respect to the model of expected returns are estimated from time-series regressions based on daily data over the previous year. In the value-weighted case, abnormal industry returns are weighted by the relative market capitalization of industries. The interquartile range is computed as the 75th percentile of the cross-section of daily abnormal industry returns minus the 25th percentile. Returns on the 100 portfolios formed on book-to-market and size as well as on the 25 portfolios formed on size and short-term reversal are taken from Kenneth French's data library. In Panel B, standard errors (in parentheses) are adjusted for heteroskedasticity and clustered by day of pair divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Description of Alternative Distraction Proxies

Proxy Label	Proxy availability	Computation Scheme	Expected returns	Market Segments
Baseline Distraction Proxy	1/1962-12/2008	Volatility-weighting of absolute abnormal returns	OLS Market Model	49 Fama French Industries
Alternative Distraction Proxy 1	1/1961-12/2008	Equal-weighting of absolute abnormal returns	OLS Market Model	49 Fama French Industries
Alternative Distraction Proxy 2	1/1961-12/2008	Value-weighting of absolute abnormal returns	OLS Market Model	49 Fama French Industries
Alternative Distraction Proxy 3	7/1964-12/2008	Equal-weighting of absolute abnormal returns	Four-Factor Model	49 Fama French Industries
Alternative Distraction Proxy 4	7/1964-12/2008	Value-weighting of absolute abnormal returns	Four-Factor Model	49 Fama French Industries
Alternative Distraction Proxy 5	7/1965-12/2008	Volatility-weighting of absolute abnormal returns	Four-Factor Model	49 Fama French Industries
Alternative Distraction Proxy 6	1/1961-12/2008	Interquartile range of raw abnormal returns (Q3 - Q1)	OLS Market Model	49 Fama French Industries
Alternative Distraction Proxy 7	7/1964-12/2008	Interquartile range of raw abnormal returns (Q3-Q1)	Four-Factor Model	49 Fama French Industries
Alternative Distraction Proxy 8	1/1960-12/2008	Regression approach with raw returns as in Stivers/Sun (2010)	None	49 Fama French Industries
Alternative Distraction Proxy 9	7/1965-12/2008	Volatility-weighting of absolute abnormal returns	OLS Market Model	100 book-to-market x size
Alternative Distraction Proxy 10	7/1964-12/2008	Volatility-weighting of absolute abnormal returns	OLS Market Model	25 size x short-term reversal

Panel B: One Day Waiting, Full Sample Period

	All	1	2	3	4	5	6	7	8	9	10	**10-1**
Attention Proxy 1	0.0097***	0.0056***	0.0067***	0.0092***	0.0082***	0.0091***	0.0097***	0.0108***	0.0116***	0.0100***	0.0133***	**0.0077*****
	(0.000315)	(0.00100)	(0.000921)	(0.000999)	(0.000991)	(0.00102)	(0.00101)	(0.00100)	(0.000917)	(0.000983)	(0.000981)	**(0.00140)**
Attention Proxy 2	0.0097***	0.0055***	0.0098***	0.0082***	0.0088***	0.0093***	0.0094***	0.0106***	0.0112***	0.0105***	0.0119***	**0.0064*****
	(0.000315)	(0.000967)	(0.00102)	(0.000970)	(0.00114)	(0.000919)	(0.00101)	(0.000947)	(0.000948)	(0.000950)	(0.000990)	**(0.00138)**
Attention Proxy 3	0.0098***	0.0065***	0.0078***	0.0071***	0.0085***	0.0085***	0.0097***	0.0121***	0.0110***	0.0110***	0.0132***	**0.0067*****
	(0.000332)	(0.00103)	(0.000967)	(0.00102)	(0.00109)	(0.00103)	(0.000989)	(0.00114)	(0.00105)	(0.000996)	(0.00101)	**(0.00145)**
Attention Proxy 4	0.0098***	0.0065***	0.0087***	0.0093***	0.0091***	0.0100***	0.0092***	0.0098***	0.0101***	0.0116***	0.0119***	**0.0053*****
	(0.000332)	(0.00104)	(0.00102)	(0.00107)	(0.00113)	(0.00102)	(0.00107)	(0.00102)	(0.00106)	(0.000983)	(0.000997)	**(0.00144)**
Attention Proxy 5	0.0099***	0.0067***	0.0084***	0.0052***	0.0110***	0.0078***	0.0096***	0.0126***	0.0099***	0.0113***	0.0135***	**0.0068*****
	(0.000336)	(0.00104)	(0.00101)	(0.00102)	(0.00102)	(0.00108)	(0.00112)	(0.00107)	(0.00111)	(0.000978)	(0.00102)	**(0.00146)**
Attention Proxy 6	0.0097***	0.0062***	0.0075***	0.0076***	0.0091***	0.0094***	0.0090***	0.0113***	0.0103***	0.0118***	0.0127***	**0.0065*****
	(0.000319)	(0.00101)	(0.000983)	(0.000958)	(0.000958)	(0.00101)	(0.00101)	(0.000983)	(0.00101)	(0.00102)	(0.000997)	**(0.00142)**
Attention Proxy 7	0.0098***	0.0056***	0.0092***	0.0093***	0.0081***	0.0064***	0.0097***	0.0104***	0.0114***	0.0111***	0.0141***	**0.0085*****
	(0.000332)	(0.000979)	(0.00104)	(0.00101)	(0.00102)	(0.00118)	(0.00100)	(0.00108)	(0.000945)	(0.00101)	(0.00104)	**(0.00143)**
Attention Proxy 8	0.0097***	0.0079***	0.0083***	0.0095***	0.0082***	0.0093***	0.0097***	0.0108***	0.0102***	0.0103***	0.0120***	**0.0041*****
	(0.000315)	(0.00106)	(0.000965)	(0.00101)	(0.00102)	(0.00104)	(0.000910)	(0.000937)	(0.00105)	(0.000998)	(0.000938)	**(0.00142)**
Attention Proxy 9	0.0099***	0.0069***	0.0074***	0.0094***	0.0090***	0.0077***	0.0097***	0.0094***	0.0107***	0.0129***	0.0135***	**0.0066*****
	(0.000336)	(0.000970)	(0.00107)	(0.00114)	(0.000987)	(0.00103)	(0.000981)	(0.00113)	(0.00103)	(0.00108)	(0.00103)	**(0.00141)**
Attention Proxy 10	0.0098***	0.0061***	0.0093***	0.0080***	0.0087***	0.0095***	0.0105***	0.0081***	0.0108***	0.0116***	0.0135***	**0.00742*****
	-0.000332	(0.000929)	(0.00102)	(0.00103)	(0.00109)	(0.00104)	(0.00106)	(0.00106)	(0.00101)	(0.00104)	(0.00105)	**(0.00140)**

impede capital-constraint arbitrageurs from eliminating potential mispricings, or alternatively, that the behavior of arbitrageurs themselves may amplify fundamental shocks.[12]

The appendix shows results from various regressions of pooled one-month pairs trading returns on the VIX and the distraction proxy over the period January 1990 to December 2008. We both employ raw values of the VIX as well as its yearly decile ranks, computed as for the distraction proxy.

We find that time-varying risk in arbitrage activities does appear to matter, as the VIX often shows up as a significant variable. However, the distraction proxy has a pronounced incremental impact, and remains economically and statistically highly significant.

3.4.8 Return Factor Exposure

In the following, we test whether the return difference between high and low distraction days is attributable to loadings on pervasive well-known risk factors. To transfer the event-time results of our baseline analysis to calendar time, we extend the maximum holding period from one month (our baseline approach) to six months (as in Gatev et al. (2006)). Doing so works against finding differences across distraction deciles.[13] Separately for pairs opening on high and on low distraction days, we construct a time series of daily portfolio returns which are weighted by the cumulative returns of the component pairs. Returns for both time series are then compounded to calculate monthly returns. Finally, we compute the difference between the monthly return for the high distraction portfolio and the monthly return for the low distraction portfolio. This approach might be thought of as mimicking a trading strategy designed to exploit time-varying investor attention for pairs trading in calendar time.

[12]See for instance Brunnermeier and Pedersen (2009), Gromb and Vayanos (2002), Long et al. (1990), Shleifer and Vishny (1997), Hong et al. (2011). Moreover, hedge funds' arbitrage ability has been documented to be reduced in times of market turbulence and high levels of VIX (e.g. Ben-David et al. (2011)).

[13]Note that this can be inferred from e.g. figure 3.4: Pairs opening on high (low) distraction days are characterized by a higher (lower) probability of convergence as well as higher (lower) average returns during the first few days after divergence. After roughly two weeks, pairs behave similarly. Moreover, pairs not converging within the first days are increasingly unlikely to converge at all (Engelberg et al. (2009) and figure 3.4). We extend the maximum holding period to six months to obtain smooth time-series of returns on pairs opening on high or low distraction days. As high respectively low distraction days only comprise a tenth of all trading days, simply computing time series returns with a maximum holding period of one month yields a substantial fraction of non-trading days with missing returns. However, relying on distraction quintiles instead of deciles, or simply sticking to the original approach does not change the qualitative nature of our findings.

We regress this return time series on various well-established risk factors. The first model includes the Fama and French (1993) factors. The second model additionally includes factors designed to capture persistent patterns in return autocorrelation at different time lags. Specifically, we rely on factors for short-term reversal, medium-term momentum, and long-term reversal. The inclusion of these variables is motivated by the contrarian nature of pairs trading, whose success could at least partly be subsumed by these risk premiums. The third model is augmented by the traded liquidity factor constructed in Pástor and Stambaugh (2003). It is intended to control for the strategy's exposure to the aggregate (market-wide) liquidity risk (see e.g. Avramov et al. (2006), Engelberg et al. (2009)). For data availability reasons, this model starts in January 1968, which is six years later than the other models.

Table 3.7 verifies that, in contrast to standard pairs trading[14], the distraction strategy appears market-neutral. It hardly loads notably on any risk premium. Alphas, however, are persistently statistically significant. In sum, the return difference between pairs opening on high and low distraction days does not seem attributable to standard risk factors.

3.5 Further Insights

In this section, we conduct additional tests to further establish the link between time-varying investor distraction and pairs trading profitability.

3.5.1 Time-Series Evidence

As a first test, we analyze the role of other investor distraction proxies, which are inspired by previous work. Specifically, we construct four simple alternative dummy variables for limited attention in the time series. Following DellaVigna and Pollet (2009) and Peress (2008), we employ a Friday dummy. Following the idea developed in Hirshleifer et al. (2009) and Peress (2008), we construct a variable based on the number of same-day events competing for investors' attention. To this end, we compute the number of pairs that start trading on a given day. There is considerable variation in each year and no general time

[14] In line with findings in e.g. Gatev et al. (2006), we find that the monthly return series on traditional pairs trading loads significantly negative on momentum and positive on short-term reversal.

Table 3.7: Risk Factor Exposure of High Distraction Minus Low Distraction Portfolio Returns

This table shows results from monthly calendar time-series regressions which aim at quantifying the impact of well-known risk factors on our findings. To this end, we first construct monthly returns on zero-cost portfolios separately for pairs opened on high distraction (decile 10) and low distraction (decile 1) days. To mitigate the problem of days without trading, the maximum holding period is extended to six months (as opposed to one month in the baseline approach). We distinguish between a "no waiting" and a "one day waiting" return computation scheme as outlined in the text. We then compute the difference between the return on the high distraction portfolio and the return on the low distraction portfolio. The resulting time series of monthly long-short returns is regressed on well-known risk factors. The traded liquidity factor is taken from Lubos Pástor's homepage. The remaining factor returns are obtained from Kenneth French's data library. T-statistics (in parentheses) are computed using Newey-West standard errors with six lags.

Model Specification	"no waiting"			"one day waiting"		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Start	Jan 1962	Jan 1962	Jan 1968	Jan 1962	Jan 1962	Jan 1968
Sample End	Dec 2008	Dec 2008	Dec 2008	Dec 2008	Dec 2008	Dec 2008
Observations	564	564	492	564	564	492
Market Factor	-0.0633	-0.0581	-0.0324	-0.0189	-0.0122	0.0058
t-statistic	(-1.23)	(-1.10)	(-0.59)	(-0.44)	(-0.28)	(0.13)
Size Factor	0.0480	0.0586	0.0957*	0.0638	0.0682	0.0961*
t-statistic	(1.07)	(1.21)	(1.93)	(1.44)	(1.42)	(1.92)
Value Factor	-0.0780	-0.0560	-0.0300	-0.0556	-0.0362	-0.0192
t-statistic	(-1.52)	(-0.90)	(-0.49)	(-1.08)	(-0.63)	(-0.33)
Momentum Factor		0.0270	0.0179		0.0482	0.0371
t-statistic		(0.59)	(0.38)		(1.12)	(0.84)
Short Term Reversal Factor		-0.0094	-0.0263		0.0017	-0.0149
t-statistic		(-0.18)	(-0.48)		(0.032)	(-0.27)
Long Term Reversal Factor		-0.0322	-0.0519		-0.0152	-.02308
t-statistic		(-0.42)	(-0.67)		(-0.23)	(-0.34)
Liquidity Factor			0.0416			0.0588
t-statistic			(0.81)			(1.30)
Alpha	**0.0038*** **	**0.0035** **	**0.0037** **	**0.0030** **	**0.0025***	**0.0029** **
	(2.79)	**(2.48)**	**(2.41)**	**(2.39)**	**(1.88)**	**(2.04)**

trend. The latter is not surprising, as the number of pairs eligible for trading remains constant after the first six months of the sample period, which we exclude. However, the number of opening pairs is significantly positively correlated (0.25) with distraction proxy decile ranks. Therefore, we rely on the residuals from a regression of the logarithmized number of diverging pairs on distraction proxy decile ranks. Finally, we condense this information into a dummy variable. We use the top and bottom quintile to identify days with an unexpectedly large number (dummy=1) or small number (dummy=0) of newly opening pairs. With regard to the third and fourth proxy, we follow Hou et al. (2009) and Karlsson et al. (2009) who provide evidence that investors tend to be less attentive during down market periods. We rely on NBER recession dates and create a dummy variable that takes the value of one if NBER classifies a month as recession. We also create an alternative dummy that is one if the cumulative three year value-weighted market return is negative and zero otherwise.

We then imitate our baseline approach of section 3.3 by regressing pair returns separately on each of these limited attention dummies (specification 1) as well as additionally on the full set of control variables used in model 8 of table 3.3, including the distraction proxy decile rank (specification 2). As we have four alternative proxies, two regression specifications, and two return computation schemes, we run 16 regressions in total. Each of the attention dummies is constructed in a way that a positive coefficient is expected. The main findings are presented in panel A of table 3.8.

As predicted, the coefficient is positive in all 16 cases.[15] The persistent positive sign of the coefficients is broadly consistent with the idea of limited attention affecting the relative efficiency of linked assets, although most proxies lack significance once one controls for calendar, industry, market and pair characteristics. In all multivariate regressions, however, the distraction proxy decile rank remains highly statistically and economically significant, suggesting that its explanatory power tends to be greatest.

Given these insights, we explore whether the sensitivity of pairs trading returns to distraction proxy decile ranks becomes even higher once one considers the proxy's possible interaction with the attention proxies inspired by previous work. Specifically, consider

[15] By far the strongest effect, both statistically and economically, is found for the attention proxy based on NBER recession periods. Note, however, that in contrast to e.g. decile ranks of our novel proxy, recession months are far from being uniformly distributed across sample years.

Table 3.8: Further Tests (I): Investor Distraction and Pairs Trading Profitability

Panel A reports the impact of alternative limited attention dummies on the profitability of pairs trading. Details about the construction of each proxy are given in the text. Specification 1 displays findings from univariate tests. In specification 2, control variables correspond to those used in model 8 of table 3.3. Standard errors are adjusted for heteroscedasticity and clustered by day of pair divergence. T-statistics are reported in parentheses. Panel B shows interaction effects and corresponding t-statistics. In specification 1 (2), we regress the one-month event-time pairs return on the distraction proxy decile rank, an alternative limited attention dummy as in panel A, and on the interaction effect (as well as on the full set of controls). Panel C shows the implied percentage increase in return difference between high and low distraction scenarios when benchmarked against the baseline findings in tables 3.2 and 3.3. High (low) distraction scenarios are defined as days satisfying both distraction proxy decile rank 10 and alternative limited attention dummy=1 (distraction decile 1 + alternative dummy=0). In Panel D, we compare mean and median returns of pairs opening on the last trading day before federal holidays with mean and median returns of pairs opening on any other day of the year. The table shows the fraction of years in which returns on pre-holiday pairs trading are higher. P-values (in parentheses) are computed from one-sided binominal probability tests with an assumed yearly success rate of 50%. *Excess probability of convergence* is computed as the difference between the fraction of converging pairs that diverged immediately before the federal holiday and the fraction of converging pairs that diverged on any other day of the year. T-statistics are reported in parentheses. In all panels, statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Impact of Limited Attention Proxies Derived from Previous Work

Model specification	Return Computation	Fridays	No. pairs opening	NBER recessions	3 year market return
Specification 1 (no further controls)	No waiting	0.0006	0.0046***	0.0113***	0.0066***
		(0.74)	(4.20)	(10.50)	(6.36)
	One day waiting	0.0002	0.0033***	0.0090***	0.0055***
		(0.21)	(3.18)	(8.99)	(5.51)
Specification 2 (full set of controls)	No waiting	0.0010	0.0002	0.0050**	0.0006
		(0.42)	(0.18)	(2.55)	(0.37)
	One day waiting	0.0006	0.0007	0.0041**	0.0004
		(0.27)	(0.68)	(2.37)	(0.22)

Panel B: Interaction Effects from Combining the Distraction Proxy with Limited Attention Dummies Derived from Previous Work

Model specification	Return Computation	Fridays	No. pairs opening	NBER recessions	3 year market return
Specification 1 (no further controls)	No waiting	0.0004	0.0006	0.0006*	0.0004
		(1.54)	(1.50)	(1.78)	(1.21)
	One day waiting	0.0005*	0.0003	0.0004	0.0003
		(1.71)	(0.81)	(1.25)	(1.03)
Specification 2 (full set of controls)	No waiting	0.0004	0.0002	0.0003	0.0002
		(1.34)	(0.62)	(0.79)	(0.79)
	One day waiting	0.0004	0.0002	0.0002	0.0004
		(1.50)	(0.43)	(0.69)	(1.34)

Panel C: Implied Percentage Increase in the Return Difference between High Distraction and Low Distraction Scenarios

Model specification	Return Computation	Fridays	No. pairs opening	NBER recessions	3 year market return
Specification 1 (no further controls)	No waiting	28.50%	51.47%	139.28%	80.13%
	One day waiting	29.68%	50.86%	150.22%	94.45%
Specification 2 (full set of controls)	No waiting	2.93%	4.59%	135.09%	30.17%
	One day waiting	2.25%	9.73%	154.04%	35.36%

Panel D: Relative Success of Pre-Holiday Pairs Trading

Pairs Trading Returns	Thanksgiving Day	Christmas Day	New Year's Day	Independence Day
Mean	61%*	70%***	72%***	51%
Median	55%	63%*	70%***	53%
Excess probability of convergence	0.42%	7.39%*	15.77%***	5.61%
(baseline probability: 36.15%-36.3%)	(0.10)	(1.68)	(3.67)	(1.35)
Pairs Trading Returns	Washington's Birthday	Labor Day	Memorial Day	
Mean	61%*	60%	47%	
Median	46%	60%	45%	
Excess probability of convergence	-0.48%	3.87%	3.87%	
(baseline probability: 36.15%-36.3%)	(-0.14)	(1.14)	(0.94)	

the following two extreme scenarios. The first sample consists of all days with distraction decile rank 10 for which, at the same time, the alternative distraction proxy also identifies a distracting situation (e.g. a Friday or a day with a higher than expected number of diverging pairs). In these cases, attention constraints should become particularly binding. The second sample consists of all days with distraction decile rank 1 for which, at the same time, the alternative distraction proxy also identifies a situation in which attention constraints should be less binding. We expect the difference in returns of pairs opening in one of these two extreme situations to be larger than the return difference between decile 10 and decile 1 in our baseline scenario (see tables 3.2 and 3.3).

To explore this possibility, we regress one-month pairs returns on the distraction proxy decile rank, the alternative limited attention dummy variable and the interaction effect (as well as a large set of control variables). Again, we have 16 regression specifications in total. Panel B of table 3.8 shows coefficients obtained for each interaction effect, which are persistently positive as expected. Panel C shows the implied percentage change in return difference between high and low distraction scenarios, as outlined above, when benchmarked against our baseline findings. As the return difference increases in each case, findings lend further support to the notion that time-varying limited attention is an important explanatory factor for pairs trading profitability.

Next, we study whether pairs trading is particularly profitable immediately before those seven federal holidays for which NYSE has been closed over the whole sample period.[16] We expect investor distraction to be particularly high in these times. This line of reasoning is backed up by DellaVigna and Pollet (2009) who provide evidence that, even on "ordinary Fridays", investors are distracted by the upcoming weekend. It is also motivated by work on holiday effects (e.g. Frieder and Subrahmanyam (2004), Hong and Yu (2009)). We compare returns on pairs that diverge on the last trading day before the holiday with returns on pairs that open on any other day. Specifically, for each year and each holiday separately, we determine whether the mean (median) pre-holiday pairs trading return is larger or smaller than the return over the rest of the year. Panel D of table 3.8 shows the fraction of years in which pre-holiday pairs trading is more profitable. The fraction is larger than 50% in 11 out of 14 cases, and often also statistically significant. Before

[16]In chronological order of occurrence, these holidays are: New Year's Day, Washington's Birthday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, Christmas Day.

Christmas and New Year's Day, pairs trading seems particularly successful. For instance, in about 70% of all sample years, mean and median returns from pairs opening on the last trading day of the year are higher than corresponding returns over the rest of the year. This is substantially driven by a considerably higher than usual fraction of converging pairs. While on average less than 37% of pairs converge within a month, more than 50% do if they diverge immediately before New Year's Day.

3.5.2 Cross-Sectional Evidence

We finish our analysis by exploring some cross-sectional implications of our setup. Specifically, we are interested in determining which pairs react most sensitively to changes in investor distraction on the date of pair divergence. Results for the "one day waiting" ("no waiting") scheme are reported in table 3.9 (the appendix).

3.5.2.1 Alternative Assets

We expect the sensitivity to be positively related to the degree of informational frictions between the constituents of the pair. So far, we have focused on pairs with stocks from different industries. As market participants often specialize along industrial boundaries (e.g. Hong et al. (2007), Menzly and Ozbas (2010)), we expect the sensitivity to be lower for pairs consisting of stocks from the same industry. Therefore, we modify our baseline approach by again identifying the monthly top 100 pairs, but now only considering same-industry pairs. We expect the sensitivity to be even lower if we concentrate on trading pairs of whole industries instead of pairs of stocks. To verify this prediction, we identify the monthly top 20 pairs out of all possible combinations of the 49 value-weighted industries as constituents.[17]

We compute two measures of return sensitivity to time-varying investor distraction. The first measure is the return difference between pairs opening on high distraction days (decile 10) and those opening on low distraction days (decile 1). The second is the coefficient on the distraction proxy decile rank, as obtained from regressions of one-month event-time

[17] The lower number of top pairs is chosen as the maximum number of eligible pairs is only 49*48/2=1,176, and thus extremely low when compared to the baseline approach.

Table 3.9: Further Tests (II): Investor Distraction and Pairs Trading Profitability

Panel A shows the sensitivity of pairs trading returns to distraction proxy decile ranks (as observed on the day of divergence) for several samples of top pairs: The monthly top 100 pairs each consisting of firms from different industries, the monthly top 100 pairs each consisting of firms from the same industries, and the monthly top 20 pairs each consisting of two value-weighted industries. In all cases, we use the Fama/French (1997) classification with 49 industries. The first column shows the return difference between pairs diverging on high distraction days (decile 10) and pairs diverging on low distraction days (decile 1). The approach resembles the methodology used in table 3.2. The second column shows findings from regressing pairs returns on the distraction proxy decile rank. Panel B reports results from a test similar in spirit. It compares the return sensitivity for pairs whose constituent firms share (do not share) at least one business segment, as described in detail in the text. Panel C compares returns from pairs consisting only of firms with high residual media coverage and pairs consisting only of firms with low residual media coverage, as described in detail in the text. The first column compares average event-time one-month pairs trading returns. The second column shows findings from regressing pairs returns on the distraction proxy decile rank. In all panels, statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

Panel A: Impact of Investor Distraction on Pairs Consisting of Alternative Assets			
	Return computation	Diff.: Decile 10-Decile 1	Distraction Decile Rank
Top 100 pairs with stocks	one day waiting	0.00770***	0.00065***
from different industries (N=103,386)		(0.00143)	(0.0000708)
Top 100 pairs with stocks		0.0071***	0.00057***
from the same industry (N=100,726)		(0.00120)	(0.0000925)
Top 20 industry-level pairs		0.0039**	0.00033**
(N=14,180)		(0.00181)	(0.0001394)
Panel B: Pairs With and Without Common Industry Segments (since 1977)			
	Return computation	Diff.: Decile 10-Decile 1	Distraction Decile Rank
No shared industry segment	one day waiting	0.0097***	0.00073***
		(0.0023)	(0.00018)
Shared industry segment		0.0084**	0.00019
		(0.0039)	(0.00030)
Difference		0.0013	0.00054*
		(0.0038)	(0.00029)
Panel C: Pairs with High and Low Residual Media Coverage			
	Return computation	Return: All Deciles	Distraction Decile Rank
Low residual media coverage	one day waiting	0.0077***	0.0010*
		(0.0016)	(0.0006)
High residual media coverage		-0.0001	-0.0012
		(0.0030)	(0.0010)
Difference		0.0082**	0.0022*
		(0.0034)	(0.0012)

returns on the proxy such as in table 3.3. Panel A of table 3.9 shows findings supporting our line of reasoning. Compared to the baseline pairs universe, the sensitivity to the level of investor distraction is slightly lower for pairs with stocks from the same industry. It is considerably lower, though still significant.

3.5.2.2 Common Industry Segments

Panel B shows findings from a test similar in spirit. While pairs are based on firms from different industries, it is reasonable to expect that at least some of them operate, at a more disaggregated intra-firm industry level, in some common business segments. The economic link for these pairs will arguably be more visible, which renders it comparatively less likely that shocks in limited attention will cause prices to diverge. To test this hypothesis, we exploit the fact that, starting from 1977, firms have to disclose detailed financial information of any industry segment comprising more than 10% of total consolidated yearly sales. To gather this information, we rely on sales data reported in the Compustat fundamentals annual files as well as Compustat segment files, which are then merged with the CRSP data. Several screening procedures are intended to assure data quality.[18] For each pair traded at least once between January 1977 and December 2008, we determine whether firms have at least one business segment in common. We find that about 18% of pairs that satisfy all data requirements share at least one segment, where segments are again defined by the 49 Fama/French industries. We then conduct an analysis analogous to the one described in the previous paragraph. Findings reported in Panel B suggest that the return sensitivity to time-varying investor distraction appears indeed lower for pairs with same industry segments, though the difference is not always significant.

[18] See e.g. Berger and Ofek (1995) or Cohen and Lou (2011) for more detailed information about the relevant segment reporting regulations. We loosely follow these studies in imposing various criteria firms have to meet in order to enter this test. First, for a given year, firms are required to have data both in the Compustat fundamentals annual as well as segment file. Second, the sum of reported segment sales must be within 1% of total sales. Third, we exclude segment eliminations or segments with missing SIC codes.The Compustat segment file provides four-digit SIC codes for industry segments, which we transform in the 49 Fama/French industries.

3.5.2.3 Press Coverage

Finally, we explore the role of press coverage. Previous work focussing on other setups has shown that the extent of a firm's media coverage appears directly linked to the speed of information diffusion and thus to price efficiency (e.g. Peress (2008), Huberman (2001)). As press articles catch many investors' attention (e.g. Barber and Odean (2008)), disseminate information to a broad audience, and increase firm visibility (e.g. Fang and Peress (2009)), coverage should help to keep relative prices in line, also and in particular in turbulent moments. Thus, first, a highly covered pair should be less profitable than a pair that is widely neglected by the press. Second, the highly covered pair should also react less sensitive to distracting overall market situations.

To explore these predictions, we rely on the Dow Jones News Service (DJNS) database as accessible via factiva. Due to its comprehensive coverage, this database has widely been used in previous studies, and argued to be "the best approximation of public news for traders" (Chan (2003), p. 230). For each firm that meets our data requirements on pairs trading (see section 3.2.2) at some point after 1990, we collect the yearly number of news articles between 1991 and 2008.[19] As this number is strongly positively related to firm size (e.g. Fang and Peress (2009)), we perform yearly regressions of ln (1+number of news) on ln(average market capitalization). We use the yearly top and bottom quintile of the resulting yearly residuals to identify firms with particularly high or low DJNS coverage. Finally, we define a pair as being highly (lowly) covered, if both of its components are firms with high (low) coverage in the year the divergence occurs. Panel C of table 3.9 compares return characteristics for both types of pairs. Our predictions largely prove true. The one-month return difference between pairs receiving disproportionately much coverage and those widely neglected reaches at least 80 basis points. In fact, trading highly covered pairs turns out to be completely unprofitable, whereas trading lowly covered pairs is considerably more profitable than trading the average pair in 1991 to 2008. Moreover, as predicted, the pair's sensitivity to changes in the level of investor distraction is statistically and economically significantly higher for lowly covered pairs.

[19] Tetlock (2010) argues that DJNS articles before November 1996 might suffer from some measurement error and survivorship bias towards larger firms. Therefore, we have replicated the following analysis also for the subperiod 1997 to 2008. The qualitative nature of our findings does not change.

3.6 Conclusion

Understanding how markets impound information into stock prices is one of the central concerns of financial economics. We provide new insights by analyzing how the price formation of linked stocks, as identified by pairs trading techniques, is affected by investor distraction, as quantified with a novel proxy. Our results lend support to the notion that the relative efficiency of linked assets might not be stable over time, but be affected by short-term investor attention shifts. Pairs opening on high distraction days, on which exceptional market circumstances force investors to concentrate on understanding the big picture, are much more profitable than pairs opening on low distraction days. This key finding does not only hold in the US market, but also in all eight major international stock markets we study. It is economically meaningful, statistically significant, and survives a number of robustness checks. Several further tests are also consistent with the idea of investor attention constraints being an important source of friction in financial markets.

Chapter 4

Twin Stock Returns and Investor Attention Shifts

4.1 Introduction

As dual-listed companies (DLCs) pool their operations and cash-flows, their stocks should move in lockstep in frictionless, efficient markets. A substantial body of research, however, has documented that these essentially identical, but separately listed securities often sell at different prices. Fundamental factors are unlikely to fully explain the level and time-series variability of deviations from theoretical parity. By now, this phenomenon is in fact often referred to as textbook evidence of puzzling mispricing in stock markets (e.g. Barberis and Shleifer (2003), Brealey et al. (2008), Lamont and Thaler (2003b), Mullainathan and Thaler (2001), Shleifer (2000)). Previous work has revealed that noise trader risk appears to prevent arbitrageurs from quickly eliminating these apparent mispricings, so they can persist. However, the lack of riskless arbitrage opportunities does not explain why returns deviate in the first place. What exactly causes returns of twin stocks to diverge?

So far very little is known about the underlying mechanisms. The empirical literature attributes deviations primarily to consequences of some rather abstract form of noise trading in the sense of Black (1986) or Long et al. (1990). However, as Froot and Dabora (1999) stress: "The main problem with this story - here and more generally - is that the source of noise or persistent irrationality is difficult to identify." (p. 215). We aim to take a step in this direction by exploring the role of one specific potential driver of temporary return deviations: Time-varying investor attention. Our line of reasoning is quite simple and inspired by recent theoretical work. We hypothesize that investors tend to be distracted in moments where understanding the big picture is the most pressing issue. If attention-constraint investors need to pool most resources in order to assess complex unexpected market conditions, they have necessarily less resources to focus on firm-level interdependencies. In particular, they might not pay as close attention as would be necessary to keep relative returns of internationally listed twin stocks in line. Our main contribution is to present findings supportive of this view. Changes in the level of daily as well as weekly return deviations are reliably correlated with a number of conceptually quite diverse proxies deemed to measure changes in investor attention. Return deviations are significantly higher (lower) than usual in moments of high (low) investor distraction.

This is arguably surprising. In essence, twin stocks represent almost perfect substitutes, typically large and liquid, which simply trade in two different countries. Investors should be reasonably expected to always be aware of the blatant, contractual, and sometimes long-standing economic relationship these firms have. On the other hand, there is some reason to ex ante believe that attention constraints might be binding enough to cause returns of even twin stocks to drift apart. First, and in contrast to other settings, the literature has already established strong evidence of limits to arbitrage. This is a necessary prerequisite for the possibility of identifying traces of not fully rational investor behavior in stock returns. Second, there is first evidence that attention constrained investors fail to take economic links into account, which, however, are arguably less clear-cut than in our study. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) demonstrate that investors temporarily neglect well-defined customer-supplier links at the firm or industry level, thereby causing return predictability. Klibanoff et al. (1998) show that closed-end country funds' prices react more quickly than usual to changes in fundamentals when prominently broadcasted, but salient, country-specific news catches investors' attention.

Designing promising proxies for (changes in) investor distraction is a challenge for any empirical work, as attention allocation in financial markets is not observable. Our approach is twofold. First, we design a set of baseline proxies, which build on the intuition of recent models on information processing in the presence of attention constraints. Second, we also investigate the role of several previously proposed, intuitive, and conceptually different proxies for investor distraction in the time-series.

Models as Peng and Xiong (2006) or Peng (2005) propose that market participants aim to optimally allocate their finite attention across several aggregation levels. The allocation is based on priority and urgency. Market- and sector-level information typically have the largest impact on the investors' overall portfolio and therefore get most attention. Remaining resources are used to process more disaggregate, firm-level information. A natural time-series implication of this setup is that investors' attention towards such information is not stable, but subject to temporary shifts. As Peng and Xiong (2006) put it: "In severely constrained cases, the investor allocates all attention to market- and sector-level information and ignores all the firm-specific data" (p. 565). Inspired by this idea, we construct a set of baseline distraction proxies whose goal is to capture the unexpected daily information load investors face in order to timely assess the general market situation. Their design closely follows the approach proposed in chapter 3. Building on the assumption that information shocks are partly reflected in abnormal returns, we construct country-specific proxies by condensing the magnitude and dissemination of unanticipated daily return shocks in a broad range of market segments. We then perform yearly decile sorts of the resulting values. Finally, we combine the information contained in the two country-specific proxies relevant for each twin under consideration. We employ several approaches to distinguish between low distraction days (i.e. low decile ranks) and high distraction days (i.e. high decile ranks).

Univariate regressions reveal that average currency-adjusted differences in daily returns are 35 to 60 basis points higher on high distraction days than on low distraction days. At the weekly frequency, the difference is even 45 to 70 basis points. These values correspond to roughly 25% to 50% of the typical standard deviation of return discrepancies. The link can be identified for each of the twelve international and quite heterogeneous DLCs we study. In multivariate regressions, we aim at controlling for comovement effects with domestic stock market return shocks, for imperfect synchronization of return data, for changes in arbitrage risk as well as for variables potentially related to the distraction proxies. The latter retain their strong statistical significance with coefficients close to two thirds in magnitude. This finding survives a number of sensitivity checks. Moreover, it largely carries over to the price perspective. Price deviations from theoretical parity tend to be somewhat higher (lower) than usual in moments of high (low) investor distraction.

To address concerns about the ability of our baseline proxies to pick up pure attention effects, we further test intuitive alternative measures proposed in earlier work. In line with our expectations, return deviations are higher (lower) than usual on Fridays (Mondays). They are more pronounced in down market periods. Moreover, they are higher when many corporate events in the respective stock markets compete for investors' attention.

In a related out of sample setting, we finally investigate return deviations of 23 liquid US dual-class shares (e.g. Schultz and Shive (2010)). These shares differ in voting rights, but not in cash-flow rights. Findings again appear in line with a limited attention story.

The remainder of this chapter is organized as follows. Section 4.2 gives background information about DLCs and provides an overview of related research. Section 4.3 discusses our data and the construction of baseline distractions proxies. Section 4.4 provides main empirical findings. Section 4.5 shows results from tests designed to further investigate the role of limited attention. Section 4.6 concludes.

4.2 Background and Related Literature

The terms "dual-listed companies" or "Siamese twin stocks" refer to a setting where two requirements are met. Two firms, typically incorporated in different countries, have contractually agreed to combine their operations and to split all of their current and future cash-flows in a fixed proportion.[1] Despite this quasi merger, however, these firms remain separate entities and have distinct legal identities. They have their own stock exchange listings in their own countries and they retain their own investor clienteles.

Consider, for example, the arguably most widely recognized twin stocks Royal Dutch and Shell, which are extensively discussed in Rosenthal and Young (1990) and Froot and Dabora (1999). Until their unification in July 2005, Royal Dutch and Shell were independent firms incorporated in the Netherlands and UK, respectively. While they traded in principle on several exchanges, they did predominantly so in their home countries, and, in the case of Royal Dutch, in the US. Based on a long-standing merger agreement from 1907, all cash flows, adjusted for corporate taxes and control rights, were split so that Royal Dutch

[1] See Bedi et al. (2003) for a discussion of why companies choose DLC structures and Jong et al. (2009) for a description of different types of DLCs.

shares always received 60 percent and Shell shares always received 40 percent. Froot and Dabora (1999) argue that there was a considerable amount of public and readily available information clarifying this very fundamental relationship. Consequently, in efficient and frictionless markets, dividing the market value of Royal Dutch by the market value of Shell should result in a value of 1.5 at any point in time.

In essence, twin stocks are two securities with nearly identical claims and can thus be considered close-to-perfect substitutes. When investigating price discovery for these stocks, one does not have to make strong assumptions about the properties of fundamentals. This unique setting allows to circumvent the joint hypothesis problem (Fama (1998)), which plagues many other tests of market efficiency. DLCs therefore provide an interesting opportunity to deepen our understanding of how markets actually work.

A number of papers have explored these special cases and thereby established some key facts. Starting with Rosenthal and Young (1990), several studies have identified strong and persistent deviations from the ratio of adjusted cash flows for a number of twin stocks. Attempts to fully rationalize this phenomenon have largely failed. Rosenthal and Young (1990), Froot and Dabora (1999) as well as Jong et al. (2009) collectively show that fundamental factors such as currency risk, voting rights, legal issues, liquidity, taxation, institutional obstacles, short-sale constraints, and different time zones are not the major determinant of deviations from theoretical parity. Instead, Froot and Dabora (1999) as well as Bedi et al. (2003) demonstrate that the return on each twin stock comoves excessively with the market on which the stock is traded most.[2] In the overall picture, the behavior of twin stocks represents "a deep challenge to the efficient markets hypothesis" (Shleifer (2000), p. 31). Another key insight previous work has gained is to understand that arbitrage appears limited in these cases. While there is hardly any fundamental risk, and while there are no major implementation costs, arbitrageurs are exposed to substantial noise trader risk (e.g. Shleifer (2000), Barberis and Shleifer (2003)). Cumulative return deviations show considerable time-series variation. It is hardly predictable when

[2]This finding might be regarded as being in line with implications of limited investor attention. Theoretical work such as Barberis and Shleifer (2003) or Barberis et al. (2005) assumes that, to simplify the complexity of portfolio decisions, investors tend to group assets into categories and then trade them at the level of these categories. Alternatively, investors might have preferred habitats, i.e. trade primarily a specific subset of all available securities. Both mechanisms can delink returns from fundamentals. In this sense, our analysis might be considered as an attempt to provide direct evidence of the impact of investor attention shifts, controlling for and going above and beyond what has been documented before.

their prices will converge again. Scruggs (2007) and Jong et al. (2009) demonstrate in detail that arbitrage trading strategies bear large risks, which might prevent rational investors from aggressively betting against the apparent mispricing (see also Long et al. (1990), Shleifer and Vishny (1997)). These limits to arbitrage are able to explain why deviations from theoretical parity might persist, yet they are not able to explain why these deviations arise in the first place.

There appears to be consensus in the literature that at least some part of the seemingly abnormal behavior of twin stocks is likely to be the result of some form of noise trading. An important question, however, remains largely unanswered: Why do investors at least temporarily fail to take the seemingly obvious fundamental relationship between twin stocks into account? Why is the law of one price violated?

A partial answer might be found in another stream of theoretical and empirical research, which highlights the importance of attention constraints in finance. This literature builds on extensive evidence from psychological research stressing that attention is a scarce cognitive resource. Focussing attention on one task necessarily goes along with a substitution of cognitive resources from other tasks (Kahneman (1973)).

On the empirical side, most research so far has concentrated on the return predictability of individual assets. The common line of arguments here is that cognitively overloaded investors tend to neglect value-relevant information, thereby inducing predictable price drifts. For example, DellaVigna and Pollet (2009), Hirshleifer et al. (2009), Hou et al. (2009) as well as Peress (2008) all analyze the market reactions to earnings announcement. All studies conclude that immediate reactions are weaker, but post-announcement abnormal returns are higher in moments of high investor distraction.

The impact of attention constraints is not restricted to this specific corporate event. Instead, the literature suggests that stressing the implications of limited investor attention is a powerful approach, which can help to uncover and better understand a broad spectrum of return phenomena. For example, it appears to matter in the context of large merger announcements (Louis and Sun (2010)), of long-run industry return predictability (DellaVigna and Pollet (2007)), and even of information transfer from the industry to the overall market level (Hong et al. (2007)).

A few studies so far have concentrated on the relative pricing efficiency of fundamentally linked assets, and are thus particularly related to our study. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) show that attention constraints prevent investors from immediately processing value-relevant information for firms or industries linked through the supply chain. As a consequence, returns of supplier and customer firms cross-predict each other. Klibanoff et al. (1998) show that the prices of closed-end funds better reflect their net asset value if salient news about the country under consideration is presented in an attention-grabbing matter on the front page of the New York Times.

Overall, the literature lends supports to assumption that attention constraints might potentially be binding enough to matter even for the case of twin stocks.

4.3 Data and Descriptive Statistics

4.3.1 Twin Stocks

Our data on in total twelve DLCs is obtained from Mathijs A. van Dijk's homepage at http://mathijsavandijk.com/dual-listed-companies. This ensures data quality and facilitates comparison with previous work, as it has, for instance, already been the basis of Jong et al. (2009). Table 4.1 shows sample characteristics.

The twin stocks are heterogeneous in several dimensions, proposing a hurdle for the identification of any common factors affecting their behavior. For instance, the twelve DLCs represent eight different country pairs and nine stock markets in total: Australia, Belgium, Finland, France, the Netherlands, Sweden, Switzerland, the UK, and the USA. There are three Anglo-Dutch twins (Royal Dutch/Shell, Unilever, Elsevier/Reed International) as well as three Australian-Anglo twins (Rio Tinto, BHP Billiton, Brambles Industries). The remaining twins represent unique country combinations.

The start date of the sample period for each DLC is determined by the joint availability of distraction proxy data (see below) and return data on the twins (i.e. the post-merger period). The earliest sample start is January 1991 and available for the Anglo-Dutch twins. The sample period ends on the earlier of two dates: 20 trading days before the unification announcement or on October, 3, 2002. The latter corresponds to the end of the sample

Table 4.1: Overview of Dual-Listed Companies

This table displays the twelve dual-listed companies studied in this section. *Stock market* 1 and *Stock market* 2 denote the countries in which the parent companies are listed. *Time diff* refers to the time differential (in hours) between both countries. Twin stocks are defined in a way that stock market 1 (twin 1) is always in the same or an earlier time zone that stock market 2 (twin 2). The start date of the sample period for each twin is determined by max(start of the availability of distraction proxy data, start of the availability of return data for the twins (i.e. the merger date)). The end date of the sample period is determined by min(20 days before unification announcement, 3 October 2002). The latter corresponds to the end of the sample period in De Jong et al. (2009), whose data we rely on. *Obs* refers to the total number of daily return observations.

Twin 1/Twin 2	Stock market 1	Stock market 2	Time diff	Sample start	Reason	Sample end	Reason	Obs
Royal Dutch/Shell	Netherlands	UK	-1	2-Jan-91	Proxy availability	3-Oct-02	End of sample period	3,067
Unilever	Netherlands	UK	-1	2-Jan-91	Proxy availability	3-Oct-02	End of sample period	3,067
ABB	Switzerland	Sweden	0	3-Jan-94	Proxy availability	7-Jan-99	Unification	1,309
Smithkline Beecham	UK	USA	-5	2-Jan-91	Proxy availability	22-Jan-96	Unification	1,279
Fortis	Netherlands	Belgium	0	4-Jan-93	Proxy availability	31-Jul-00	Unification	1,976
Elsevier/Reed International	Netherlands	UK	-1	4-Jan-93	Merger date	3-Oct-02	End of sample period	2,544
Rio Tinto	Australia	UK	-10	21-Dec-95	Merger date	3-Oct-02	End of sample period	1,771
Dexia	France	Belgium	0	19-Nov-96	Merger date	20-Aug-99	Unification	718
Merita/Nordbanken	Finland	Sweden	-1	15-Dec-97	Merger date	23-Aug-99	Unification	441
Zuerich Allied/Allied Zuerich	Switzerland	UK	-1	7-Sep-98	Merger date	20-Mar-00	Unification	401
BHP Billiton	Australia	UK	-10	29-Jun-01	Merger date	3-Oct-02	End of sample period	330
Brambles Industries	Australia	UK	-10	7-Aug-01	Merger date	3-Oct-02	End of sample period	303

period in the study of Jong et al. (2009), who provide detailed information about the timeline of each twin series. The final sample exhibits substantial cross-sectional variation in sample start, sample end, and the number of observations. Despite these apparent differences, each DLC exhibits substantial return deviations as table 4.2 reveals.[3]

Throughout the chapter, the term *return deviation* is used to refer to the absolute value of the difference between the currency-adjusted daily or weekly log returns of the twins. We report results obtained for the daily as well as weekly return frequency to obtain a comprehensive and clear picture of the role of time-varying investor distraction. Attention constraints should arguably be particular binding in the short run, which in general suggests using high frequency data. At the same time, however, these data are likely to suffer from microstructural effects. While some factors like bid-ask bounce or measures of market impact are less of an issue for the large firms under consideration, imperfect synchronization of return data matter, particularly at the daily level.[4] Weekly estimates are less affected by such imperfections. Moreover, to the extent that very short-term liquidity shocks account for the variability in return differences, they should do less so at the weekly frequency. Weekly returns are overlapping and constructed on a rolling basis over the previous five trading days.

The mean daily return difference across all observations is 1.06%, with a standard deviations of 1.10%. Non-synchronous closing prices, in particular for the the Australian-Anglo DLCs, clearly contribute to this finding. However different trading hours are by far not sufficient to explain the magnitude and the time-series variation in return deviations. First, they exist irrespective of time differences. For instance, the mean daily return difference (standard deviation) for ABB (Switzerland/Sweden), Fortis (Netherlands/Belgium) and

[3]The appendix also shows return summary statistics from the time-series perspective. Findings verify that return discrepancies exist in each sample year. While this chapter focusses primarily on return differences, the appendix also contains descriptive statistics and figures on the well-documented deviations from theoretical price parity. In the cross-section, the average absolute deviation ranges from about 4% (Dexia) to close to 12% (Zurich Allied). For all but two twins, the deviation takes on both positive and negative values. For many twins, the sign changes several times. Absolute values often take on extremes 15% or more.

[4]As can be seen from table 4.1, time differences range from 0 to 10 hours. However, as we will show, these lags are unlikely to distort our analysis. First, findings hold for the twins with no time lag. Second, findings are stronger at the weekly than at the daily frequency. Third, we control for time differences in section 4.4.2. Fourth, in section 4.5.2, we also study a sample of 23 pairs of US dual-class shares, for which time and currency effects do not play a role at all. Findings are qualitatively very similar. Fifth, see Jong et al. (2009) for evidence that different time zones and currency effects are unlikely to have noteworthy explanatory power for price deviations from theoretical parity.

Table 4.2: Descriptive Statistics of Return Deviations at the Daily and Weekly Frequency

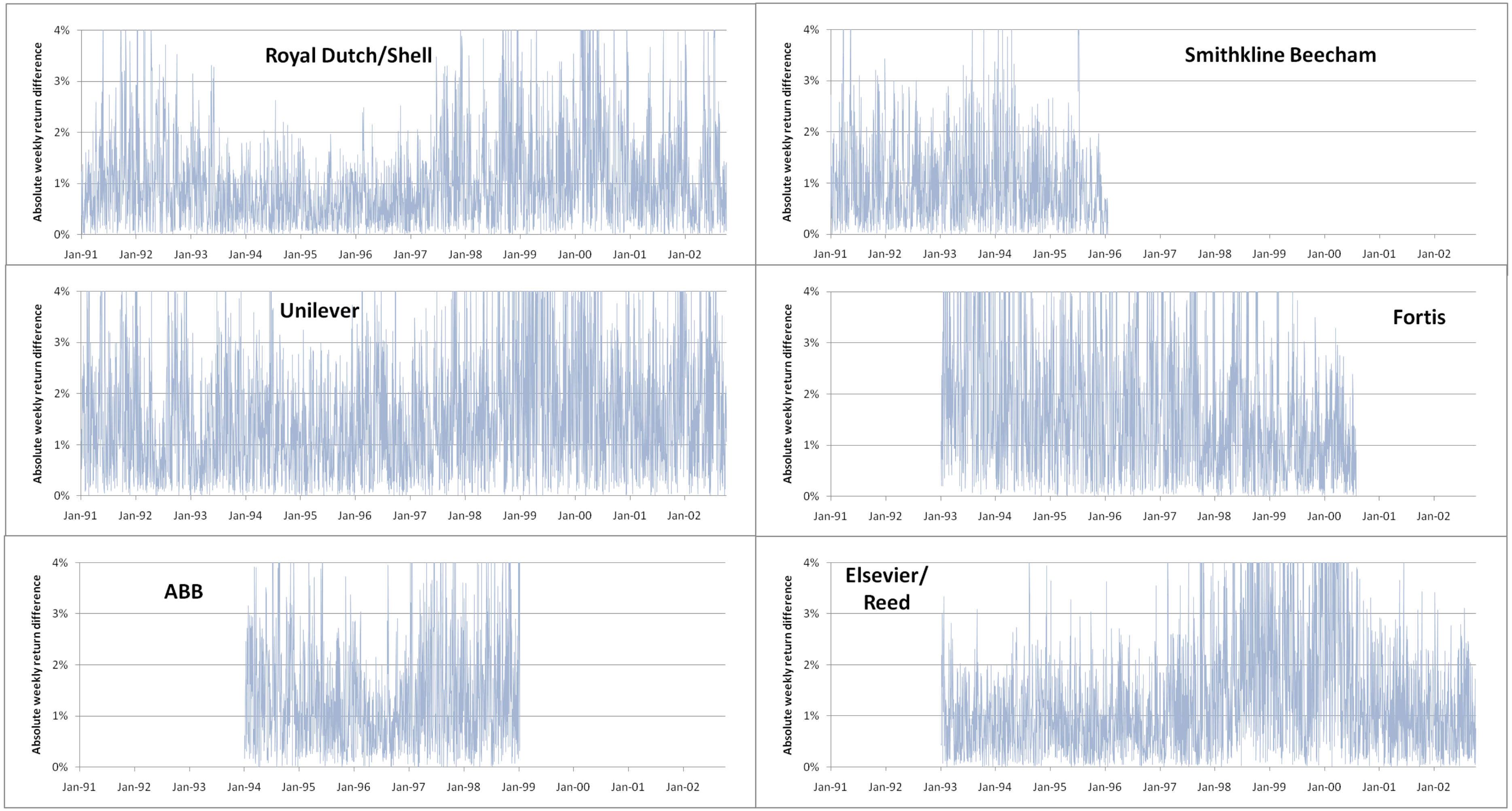
This table shows descriptive statistics of return deviations between twin stocks at the daily (panel A) and weekly (panel B) frequency. Return deviations are computed as the absolute value of the difference between the currency-adjusted daily or weekly log returns of the twins. Weekly returns are overlapping and constructed as rolling cumulative returns over the previous five trading days. *% explained* denotes the R^2 obtained from OLS time-series regressions of the absolute log return of the first twin stock on the contemporaneous currency-adjusted absolute return of the second twin (weekly frequency, panel B) as well as additionally on the lead and lag return of the second twin to account for asynchronous trading (daily frequency, panel A). This value, as well as the mean, the median, the standard deviation (StDev), and selected percentiles (P10,P50,P90) of return deviations are reported across all observations (last column) and for each DLC separately.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Time Difference	-1	-1	0	-5	0	-1	-10	0	-1	-1	-10	-10	
Sample Start	3-Apr-91	3-Apr-91	5-Apr-94	3-Apr-91	1-Apr-93	1-Apr-93	25-Mar-96	20-Feb-97	18-Mar-98	7-Dec-98	28-Sep-01	5-Nov-01	
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	
Observations	3,067	3,067	1,309	1,279	1,976	2,544	1,771	718	441	401	330	303	17,206
Panel A: Daily Data													
Mean	0.66%	1.15%	0.87%	0.73%	1.02%	0.96%	1.71%	1.11%	1.34%	1.31%	1.63%	2.46%	1.06%
StDev	0.62%	1.10%	0.76%	0.62%	0.95%	0.93%	1.53%	1.22%	1.09%	1.19%	1.42%	2.18%	1.10%
P10	0.08%	0.14%	0.12%	0.07%	0.12%	0.12%	0.21%	0.14%	0.15%	0.18%	0.23%	0.39%	0.12%
P50	0.49%	0.83%	0.66%	0.58%	0.78%	0.72%	1.31%	0.86%	1.14%	1.03%	1.23%	1.92%	0.75%
P90	1.45%	2.53%	1.90%	1.60%	2.18%	2.06%	3.72%	2.40%	2.69%	2.71%	3.39%	5.13%	2.36%
% explained	56%	26%	42%	50%	31%	47%	22%	24%	29%	51%	23%	6%	34%
Panel B: Weekly Data													
Mean	1.03%	1.61%	1.40%	1.00%	1.73%	1.31%	2.30%	1.66%	1.82%	2.25%	2.06%	4.57%	1.57%
StDev	0.93%	1.47%	1.12%	0.84%	1.53%	1.23%	1.93%	1.48%	1.47%	2.06%	1.73%	3.85%	1.56%
P10	0.13%	0.22%	0.23%	0.13%	0.20%	0.18%	0.35%	0.27%	0.27%	0.31%	0.26%	0.53%	0.20%
P50	0.80%	1.30%	1.14%	0.78%	1.33%	0.98%	1.78%	1.27%	1.52%	1.79%	1.66%	3.57%	1.14%
P90	2.21%	3.24%	2.90%	2.15%	3.77%	2.77%	4.84%	3.50%	3.67%	4.59%	4.32%	10.47%	3.40%
% explained	73%	56%	69%	78%	52%	75%	54%	45%	66%	70%	61%	15%	61%

Dexia (France/Belgium) are 0.87%, 1.02%, and 1.11% (0.76%, 0.95%, 1.22%), respectively. These values are close to the overall sample average. However, the stock markets of these twins are all in the same time zone. Moreover, deviations are also observable after 1998, when the introduction of the Euro eliminated any currency fluctuations for Dexia and Fortis. Second, and potentially more importantly, return differences are even larger if one focuses on the weekly frequency, where microstructural effects should be of much less importance. Across all observations, the average divergence in returns is 1.57%, with a standard deviation of 1.56%. Both values are about 50% higher than the values obtained at the daily frequency. In fact, weekly return deviations seem to be more pronounced and more volatile for each DLC. Figure 4.1 exemplarily depicts the time-series of weekly return deviations for the first six DLCs in our sample. They show no overall trend, but fluctuate widely throughout the sample period.

Figure 4.1: Weekly Return Deviations of Twin Stocks

This graph depicts the time-series of weekly return deviations of selected twin stocks. Return deviations are computed as the absolute value of the difference between the currency-adjusted weekly log returns of the twins. Weekly returns are overlapping and constructed on a rolling basis over the previous five trading days.



As already suggested by these findings, a considerable part of the return behavior of one twin stock cannot be explained with the behavior of the other. Simple OLS time-series regressions of the absolute weekly log return of the first twin stock on the contemporaneous currency-adjusted absolute return of the second twin yield, across all observations, a R^2 of less than two thirds.

In the overall picture, the magnitude and time-series variation of return deviations might be regarded as surprisingly large. In the following, we explore whether time-varying investor attention towards firm-level information might explain some of these findings.

4.3.2 Baseline Investor Distraction Proxies

For the construction of distraction proxies as well as control variables, we require firm-level data on a daily frequency for a number of stock markets. For the US stock market, we gather data from CRSP. Specifically, we consider all common shares (CRSP share code 10 or 11) traded on NYSE, AMEX, or NASDAQ. Our data on international stocks markets comes from the Compustat Global Daily Stock File. We impose several restrictions to assure data quality and reliability.[5]

Inspired by recent models on attention constraints, we aim at identifying days on which market participants are likely to be forced to spend more (or less) resources than usual on understanding the big picture. Obviously, implementing this idea leaves many degrees of freedom, which we address in later checks. First, we need to rely on a sensible classification scheme for market segments, as the final proxy aggregates abnormal return behavior in these segments. We here rely on industries for several reasons. Industrial boundaries group economically similar stocks (e.g. Chan et al. (2007)). At the same time, they represent informational boundaries induced by the specialization of important market participants

[5]On the firm level, only common shares of companies incorporated in the respective country are considered. Firms are required to have non-missing price, return, market capitalization, and industry membership data. We exclude very small and presumably illiquid firms with a market capitalization of less than five million Euro. Finally, we manually check extreme return outliers. On the market level, we require a full calendar year with a continuous daily return time series for at least 25 eligible stocks before considering the country under consideration. This approach is intended to be a compromise between maximizing the sample period and minimizing missing or otherwise problematic observations, which appear to be most frequent at the beginning of stock market coverage. To eliminate potentially remaining data errors, we also discard any day from the analysis for which Compustat reports price data for less than half of as many companies as on average over the preceding month.

such as analysts or institutional money managers (e.g. Hong et al. (2007), Menzly and Ozbas (2010)). Industry membership is also readily and reliably available for all international stock markets we study. Finally, findings in chapter 3 strongly suggest that main inferences are likely to be insensitive to other definitions of market segments, such as portfolios (double-) sorted on standard firm characteristics.

Baseline distraction proxies are then constructed in a five step procedure. First, we compute daily value-weighted industry-level returns for each stock market separately. For the US stock market, we thereby use the Fama and French (1997) taxonomy based on 49 industry groups.[6] For the other stock markets, we base on our analysis on the Global Industry Classification Standard (GICS). For consistency, we rely on the 10 GICS industry sectors in each stock market. Results are very similar if we make use of the more detailed 24 industry groups for the comparatively large UK stock market instead.

Second, we decompose these returns to obtain daily market segment-level return shocks for each country. Let $AR_{i,t}$ denote the shock for industry i on day t. It is computed as the absolute difference between the actual industry return $R_{i,t}$ and its expected return as implied by the market model:

$$AR_{i,t} = \mid R_{i,t} - \widehat{\alpha}_{i,t} - \widehat{\beta}_{i,t} R_{m,t} \mid \tag{4.1}$$

$\widehat{\alpha}_{i,t}$ and $\widehat{\beta}_{i,t}$ are estimated from rolling time-series regressions based on daily return data over the previous year.

Third, industry-level shocks are aggregated to obtain a single country-specific raw distraction measure $Distraction_t$. In doing so, one has to decide on how to weight each of the in total n individual shocks on a given day t. Shocks are likely to be most distracting if they are a rare event. The respective market segment should arguably obtain a higher weight. On the other hand, market segments in which investors expect frequent shocks should obtain a lower weight. To formalize this idea, we weight each industry shock $AR_{i,t}$ by the inverse of its volatility $\sigma_{i,t}$ over the previous year:

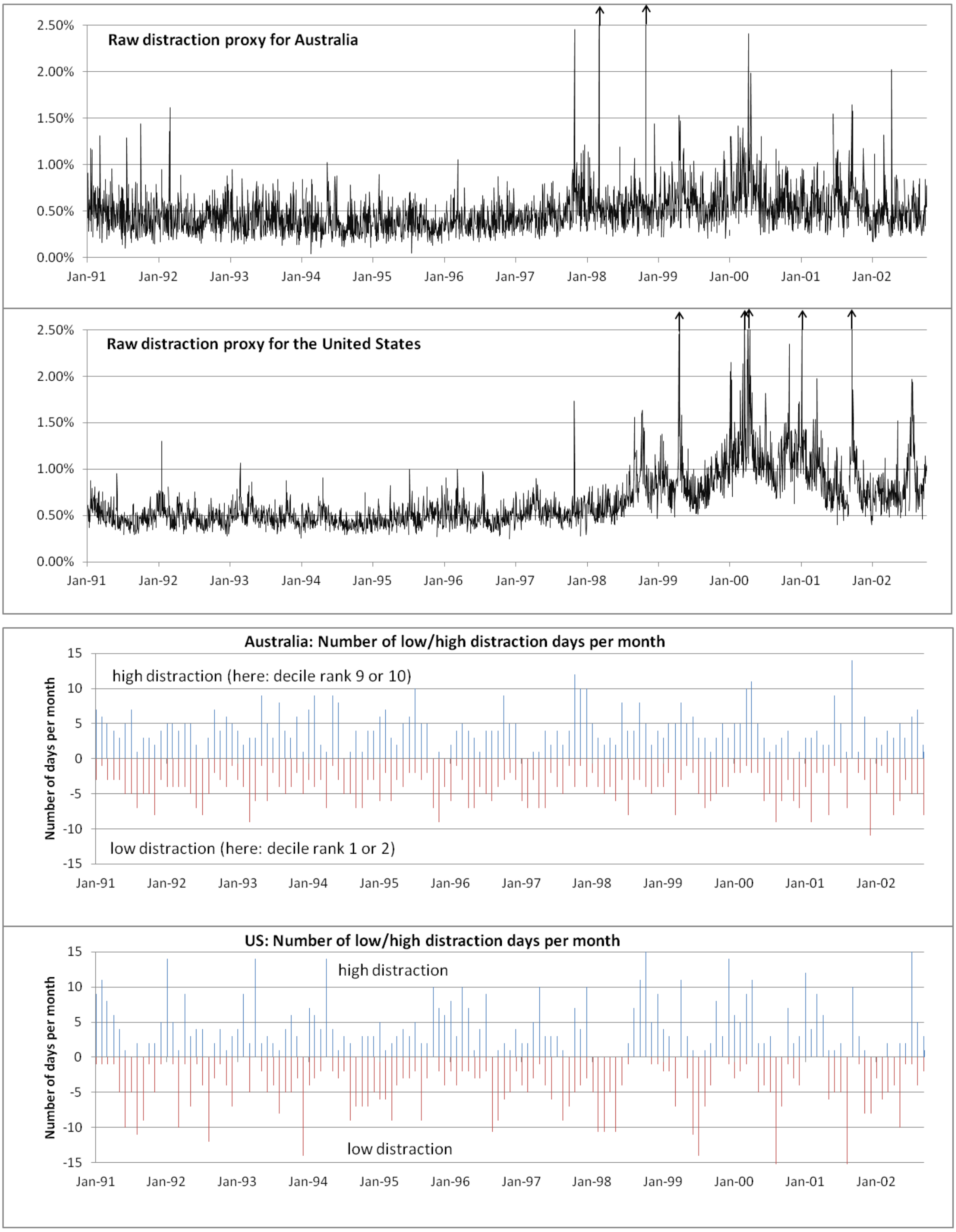
$$Distraction_t = \sum_{i=1}^{n} w_{i,t} AR_{i,t} \text{ where } w_{i,t} = \frac{\frac{1}{\sigma_{i,t}}}{\sum_{i=1}^{n} \frac{1}{\sigma_{i,t}}} \tag{4.2}$$

Figure 4.2 shows the resulting time-series exemplarily for Australia and the United States.

[6] Specifically, we use the 48 industries defined in Fama and French (1997), and group stocks that are not assigned to any industry in category 49.

Figure 4.2: Baseline Distraction Proxy Characteristics: Australia and US

These figures depict time-series characteristics of country-specific distraction proxies for Australia and the United States. The upper graphs show the evolution of the raw proxies, the lower graphs depict the number of high and low distraction days per month. High (low) distraction days are defined as deciles ranks 9 and 10 (1 and 2), as obtained from yearly deciles sorts of the country-specific raw proxy.



As a fourth step, we construct measures of relative distraction within each year, thereby making our estimates more conservative. Specifically, we perform yearly sorts of the raw proxy. For each year separately, we assign a decile-based rank to each trading day. For the construction of weekly variables, the raw distraction proxy is averaged on a rolling basis over the preceding five trading days before the decile sorts take place.

Thus, in each year, we have the same number of high and low distraction days, as obtained by an arbitrary symmetric decile rank threshold. Figure 4.2 illustrates this again for Australia and the United States. It also verifies that high and low distraction days are not heavily clustered in a given year.

Panels A (daily data) and C (weekly data) of table 4.3 display pairwise Spearman rank order correlation coefficients between country-specific distraction proxies for all sample stock markets.

Correlations fluctuate around 0.3 for daily and 0.2 for weekly data. While these values are all highly statistically significant, their moderate economic level also justifies our approach of computing attention measures for each country separately. Apparently, proxies share a common factor, but also have a country-specific component.

It is important to verify that the proxies do not simply mirror the behavior of well-known market-level measures of turbulent markets or overall uncertainty. To explore this possibility, we consider value- and equal-weighted measures of absolute domestic market returns, domestic turnover as well as domestic illiquidity.[7] We also consider the Chicago Board Options Exchange Market Volatility Index (VIX), a popular measure of the volatility implied in S&P 500 index options.[8]

Panels B (daily data) and D (weekly data) of table 4.3 demonstrate that the correlation of

[7]Our market-wide daily illiquidity proxy is inspired by Amihud (2002). We first compute stock-level illiquidity measures as the ratio of absolute daily return and daily trading volume. Second, on each day, we equally weight the values for each stock in the respective stock market to obtain a market-wide proxy. The weighting scheme follows Pástor and Stambaugh (2003), who argue that an equal-weighted (as opposed to a value-weighed) measure shows more desirable characteristics, as it is not dominated by large caps. For robustness, though, we also report a value-weighted measure. Third, we discard values above the 99th percentile to exclude outliers, which can materially affect our daily data. For the illiquidity proxy at the (overlapping) weekly frequency, we average daily market-level values on a rolling basis.

[8]We rely on this US proxy as it is the only implied volatility index available over the whole sample period. Indices for Belgium, the Netherlands, France, and the UK are available from January 2000 on. The correlation of the VIX and these indices for the period January 2000 to December 2010 ranges from 0.88 to 0.94, which justifies our approach.

Table 4.3: Correlations of Country-Specific Attention Proxies

Panel A (daily data) and panel C (overlapping weekly data) display pairwise Spearman rank order correlation coefficients between country-specific attention proxy decile ranks. Panel B (daily data) and panel D (overlapping weekly data) display correlation coefficients between attention proxy decile ranks and market-level variables. All market-level variables except for the VIX are computed for domestic stock markets. $vw(ew)$ is short for value-weighted (equal-weighted). Details on the illiquidity proxy are given in the text. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

1. Daily Values

Panel A: Pairwise correlations of country-specific attention proxies (daily values)

	US	UK	France	Switzerland	Sweden	Finland	Belgium	Netherlands
US (since Jan 91)	1							
UK (since Jan 91)	0.36***	1						
France (since Jan 91)	0.32***	0.36***	1					
Switzerland (since Jan 92)	0.26***	0.28***	0.34***	1				
Sweden (since Jan 94)	0.45***	0.32***	0.35***	0.23***	1			
Finland (since Jan 96)	0.40***	0.30***	0.35***	0.31***	0.42***	1		
Belgium (since Jan 93)	0.25***	0.28***	0.34***	0.35***	0.24***	0.36***	1	
Netherlands (since Jan 91)	0.36***	0.34***	0.45***	0.32***	0.36***	0.39***	0.29***	1
Australia (since Jan 91)	0.20***	0.23***	0.16***	0.17***	0.22***	0.24***	0.19***	0.19***

Panel B: Correlation of country-specific attention proxies with domestic market-level variables (daily values)

	VIX	Abs. return	Abs. return	Turnover	Turnover	Illiquidity	Illiquidity
Weighting scheme		vw	ew	vw	ew	vw	ew
US (since Jan 91)	0.18***	0.20***	0.26***	0.27***	0.16***	0.14***	0.05**
UK (since Jan 91)	0.10***	0.19***	0.23***	0.22***	0.14***	0.15***	0.05**
France (since Jan 91)	0.12***	0.17***	0.16***	0.22***	0.22***	0.03	0.01
Switzerland (since Jan 92)	0.13***	0.24***	0.23***	0.11***	0.06**	0.11***	0.07***
Sweden (since Jan 94)	0.11***	0.22***	0.20***	0.23***	0.14***	0.05**	0.03
Finland (since Jan 96)	0.19***	0.18***	0.23***	0.14***	0.05*	0.10***	0.11***
Belgium (since Jan 93)	0.11***	0.24***	0.21***	0.17***	-0.028	0.07***	0.03
Netherlands (since Jan 91)	0.12***	0.21***	0.23***	0.21***	0.14***	0.03	0.04*
Australia (since Jan 91)	0.07***	0.20***	0.08***	0.19***	0.08***	0.07***	0.03

2. Weekly Values

Panel C: Pairwise correlations of country-specific attention proxies (weekly values)

	US	UK	France	Switzerland	Sweden	Finland	Belgium	Netherlands
US (since Jan 91)	1							
UK (since Jan 91)	0.20***	1						
France (since Jan 91)	0.17***	0.23***	1					
Switzerland (since Jan 92)	0.15***	0.14***	0.18***	1				
Sweden (since Jan 94)	0.25***	0.14***	0.18***	0.14***	1			
Finland (since Jan 96)	0.20***	0.14***	0.17***	0.15***	0.22***	1		
Belgium (since Jan 93)	0.12***	0.15***	0.16***	0.17***	0.14***	0.16***	1	
Netherlands (since Jan 91)	0.18***	0.23***	0.21***	0.20***	0.15***	0.18***	0.16***	1
Australia (since Jan 91)	0.11***	0.13***	0.08***	0.08***	0.10***	0.15***	0.07***	0.07***

Panel D: Correlation of country-specific attention proxies with domestic market-level variables (weekly values)

	VIX	Abs. return	Abs. return	Turnover	Turnover	Illiquidity	Illiquidity
Weighting scheme		vw	ew	vw	ew	vw	ew
US (since Jan 91)	0.21***	0.24***	0.29***	0.26***	0.15***		
UK (since Jan 91)	0.15***	0.22***	0.27***	0.10***	0.17***	0.10***	0.08***
France (since Jan 91)	0.18***	0.23***	0.22***	0.15***	0.29***	0.06***	0.04*
Switzerland (since Jan 92)	0.18***	0.27***	0.24*	0.08***	0.09***	0.08***	0.09***
Sweden (since Jan 94)	0.17***	0.24***	0.22***	0.24***	0.19***	0.07***	0.04*
Finland (since Jan 96)	0.33***	0.13***	0.23***	0.11***	0.04	0.21***	0.21***
Belgium (since Jan 93)	0.17***	0.23***	0.20***	0.10***	-0.02	0.01	0.05**
Netherlands (since Jan 91)	0.20***	0.19***	0.23***	0.18***	0.16***	0.05**	0.06***
Australia (since Jan 91)	0.10***	0.16***	0.11***	0.11***	0.11***	0.03	0.07***

the distraction proxy with all these variables is (only) moderately positive. Values typically are in the range of 0.2, suggesting that the proxy combines information incorporated in a variety of standard measures deemed to represent specific aspects of unexceptional market conditions. At the same time, it appears to capture information not already incorporated in these measures, for which we later also control.

So far, we have focussed on country-specific distraction proxies. To create a measure of common inattention, we combine, in the final fifth step, the information contained in the two proxies relevant for each twin stock under consideration. For deeper insights and to assure robustness, we do so in three different ways. The first distraction proxy is simply the decile rank sum of the two country-level distraction proxies. It thus takes on values between two (low distraction) and twenty (high distraction). The second set consists of two dummy variables, a high and a low distraction dummy. The high distraction dummy takes on a value of one if, on a given day, both country-specific proxies obtain decile ranks of seven or greater. It is zero otherwise. The low distraction dummy takes on a value of one if both proxies obtain decile ranks of four or lower. It is zero otherwise. Both the high and low distraction dummy are non-zero in roughly 20% of all observations in our final sample. The third proxy set represents a more accentuated version of the second set. Consequently, we expect stronger results in the following tests. The high (low) distraction dummy now only takes on a value of one if both country-specific proxies obtain decile ranks of nine or greater (two or lower). In the pooled final sample, the likelihood of such a high or low distraction observation is roughly 6%.

In sum, our sets of distraction proxies can be expressed as follows:

$$Set\ 1_t = Proxy\ Country\ Twin1_t + Proxy\ Country\ Twin2_t \tag{4.3}$$

$$\begin{aligned} &Set\ 2_t = High\ Distraction\ Dummy_t + Low\ Distraction\ Dummy_t \\ &\quad High\ Distraction\ Dummy_t = 1 \mid (Proxy\ Country\ Twin1_t \geq 7 \cap Proxy\ Country\ Twin2_t \geq 7) \\ &\quad Low\ Distraction\ Dummy_t = 1 \mid (Proxy\ Country\ Twin1_t \leq 4 \cap Proxy\ Country\ Twin2_t \leq 4) \end{aligned} \tag{4.4}$$

$$\begin{aligned} &Set\ 3_t = High\ Distraction\ Dummy_t + Low\ Distraction\ Dummy_t \\ &\quad High\ Distraction\ Dummy_t = 1 \mid (Proxy\ Country\ Twin1_t \geq 9 \cap Proxy\ Country\ Twin2_t \geq 9) \\ &\quad Low\ Distraction\ Dummy_t = 1 \mid (Proxy\ Country\ Twin1_t \leq 2 \cap Proxy\ Country\ Twin2_t \leq 2) \end{aligned} \tag{4.5}$$

4.4 Empirical Results

4.4.1 Univariate Tests

We start with univariate tests by regressing currency-adjusted return deviations, expressed in basis points, on investor distraction proxies. We do so for each DLC and each proxy set separately. Moreover, we run regressions both at the daily and at the weekly frequency. To increase the statistical power, estimates on the weekly frequency are based on rolling regressions with overlapping daily data. To control for heteroscedasticity and autocorrelation, all standard errors are adjusted by the method of Newey and West (1987).[9] Proxies are constructed in a way that we expect a positive (negative) coefficient for high (low) distraction proxies. Tables 4.4 and 4.5 present the main findings.

Results support our hypothesis that investor attention shifts matter for keeping relative returns of twin stocks in line. At the daily (weekly) frequency, out of the in total 65 coefficients of investor distraction proxies, 62 (57) obtain the predicted sign. The majority of these coefficients is statistically significant, often at the 1% level. Judging from the p-values for the high distraction proxy in set 1 as well as from the p-values for the joint significance for the distraction dummies in set 2 and set 3, the findings appear broadly in line with our expectations for almost each DLC and each specification.

Findings are also economically meaningful. Judging from the pooled regressions, the average absolute daily (weekly) return difference is about 35 to 60 (45 to 70) basis points higher on a high distraction day than on a low distraction day. As the effect is slightly stronger for weekly regressions, our findings do not appear to be driven by microstructural effects. As a rough estimate, these values correspond to about 25% to 50% of the standard deviation of the return difference across all observations (see table 4.2).

4.4.2 Multivariate Tests

To isolate the impact of investor distraction, we include two sets of control variables in the following multivariate regressions.

[9] As proposed by Newey and West (1994), we set the lag length equal to the integer portion of $4(T/100)^{2/9}$, where T denotes the number of observations in the regression. Note that there is no adjustment for the reported R^2.

Table 4.4: Daily Return Deviations and Investor Distraction: Univariate Tests

This table shows results from univariate regressions of the absolute difference (in basis points) of daily currency-adjusted log returns on proxies for investor distraction. The independent variables in panels A to C are different sets of distraction proxies, as described in detail in the text. Regressions are run separately for each DLC as well as for the pooled sample with firm-fixed effects (last column). *HD/LD* is short for high (low) distraction. In the last row, *Predicted sign* denotes how many of the in total five distraction coefficients obtain the sign predicted by our hypotheses. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Sample Start	2-Jan-91	2-Jan-91	3-Jan-94	2-Jan-91	4-Jan-93	4-Jan-93	21-Dec-95	19-Nov-96	15-Dec-97	7-Sep-98	29-Jun-01	7-Aug-01	(firm-fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)
Panel A: Distraction Proxy Set 1													
HD Proxy	1.78***	3.27***	2.16***	1.01**	2.12***	2.68***	5.57***	2.66**	2.29	4.68**	3.92**	9.11**	2.89***
	(5.71)	(6.49)	(3.08)	(2.15)	(3.73)	(4.65)	(4.42)	(2.57)	(1.48)	(2.25)	(2.15)	(2.36)	(11.66)
P-Value	0.000***	0.000***	0.002***	0.032**	0.000***	0.000***	0.000***	0.010***	0.14	0.025**	0.033**	0.019**	0.000***
Panel B: Distraction Proxy Set 2													
HD Dummy	18.97***	22.24***	26.44***	-0.21	11.51	21.92***	58.99***	21.22*	-12.60	39.50*	59.23**	128.90**	24.87***
	(5.02)	(3.78)	(3.30)	(-0.04)	(1.60)	(3.48)	(3.77)	(1.78)	(-0.62)	(1.74)	(2.03)	(2.52)	(8.29)
LD Dummy	-6.14**	-18.20***	-3.23	-9.18**	-13.67***	-11.37**	-11.48	-7.61	-32.21**	1.03	-0.03	-14.48	-11.22***
	(-2.36)	(-3.75)	(-0.57)	(-2.15)	(-2.65)	(-2.54)	(-1.26)	(-0.88)	(-2.37)	(0.06)	(-0.00)	(-0.43)	(-5.72)
P-value joint sign.	0.000***	0.000***	0.003***	0.098*	0.004***	0.000***	0.000***	0.089*	0.058*	0.222	0.109	0.034**	0.000***
Panel C: Distraction Proxy Set 3													
HD Dummy	25.49***	28.59***	34.88***	5.05	16.12	37.15***	89.13***	58.80**	7.82	53.06	86.72**	163.74**	39.18***
	(3.61)	(2.94)	(2.78)	(0.62)	(1.49)	(2.94)	(3.48)	(2.05)	(0.31)	(1.63)	(1.99)	(2.35)	(7.40)
LD Dummy	-10.62***	-28.29***	-3.98	-17.86***	-6.85	-18.42***	-27.67**	-11.23	-21.01	-43.43**	-42.33	-72.44*	-19.17***
	(-2.63)	(-4.50)	(-0.35)	(-3.04)	(-0.95)	(-2.88)	(-2.34)	(-0.75)	(-0.78)	(-2.02)	(-1.35)	(-1.86)	(-6.47)
P-value joint sign.	0.000***	0.000***	0.020**	0.007***	0.217	0.000***	0.000***	0.090*	0.707	0.040**	0.060*	0.009***	0.000***
Predicted Sign	5/5	5/5	5/5	4/5	5/5	5/5	5/5	5/5	4/5	4/5	5/5	5/5	5/5
Mean Durbin Watson	1.54	1.44	1.75	1.61	1.69	1.50	1.50	1.64	1.47	1.51	1.85	1.73	
Mean Adj. R^2	0.02	0.01	0.02	0.01	0.01	0.01	0.03	0.01	0.00	0.02	0.02	0.04	0.13

Table 4.5: Weekly Return Deviations and Investor Distraction: Univariate Tests

This table shows results from univariate regressions of the absolute difference (in basis points) of weekly currency-adjusted log returns on proxies for investor distraction. The independent variables in panels A to C are different sets of distraction proxies, as described in detail in the text. Regressions are run separately for each DLC as well as for the pooled sample with firm-fixed effects (last column). *HD/LD* is short for high (low) distraction. In the last row, *Predicted sign* denotes how many of the in total five distraction coefficients obtain the sign predicted by our hypotheses. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Sample Start	3-Apr-91	3-Apr-91	5-Apr-94	3-Apr-91	1-Apr-93	1-Apr-93	25-Mar-96	20-Feb-97	18-Mar-98	7-Dec-98	28-Sep-01	5-Nov-01	(firm fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)
Panel A: Distraction Proxy Set 1													
HD Proxy	3.01***	3.19***	2.13**	0.46	2.18**	4.04***	5.26***	2.57*	2.36	9.57**	8.67***	11.28*	3.54***
	(4.89)	(4.07)	(2.25)	(0.64)	(2.02)	(4.02)	(3.60)	(1.84)	(1.40)	(2.39)	(3.75)	(1.68)	(9.25)
P-value	0.000***	0.000***	0.024**	0.525	0.043**	0.000***	0.000***	0.067*	0.162	0.018**	0.000***	0.094*	0.000***
Panel B: Distraction Proxy Set 2													
HD Dummy	32.15***	21.93**	17.61*	3.58	-10.49	36.85***	52.95***	26.09*	44.07**	103.55**	88.36**	226.05***	31.97***
	(4.32)	(2.19)	(1.66)	(0.45)	(-0.92)	(3.03)	(2.97)	(1.96)	(1.97)	(2.36)	(2.52)	(2.84)	(7.05)
LD Dummy	-7.38	-13.41*	-11.32	5.32	-38.60***	-17.12***	-13.80	-1.43	13.18	-7.74	-23.38	68.79	-12.08***
	(-1.50)	(-1.89)	(-1.27)	(0.78)	(-3.37)	(-2.94)	(-1.12)	(-0.09)	(0.74)	(-0.27)	(-1.01)	(1.06)	(-3.72)
P-value joint sign.	0.000***	0.003***	0.078*	0.697	0.003***	0.000***	0.004***	0.120	0.136	0.048**	0.006***	0.017**	0.000***
Panel C: Distraction Proxy Set 3													
HD Dummy	36.46***	35.62***	43.96**	-5.19	26.46	61.61***	74.48**	39.61***	16.93	173.09**	101.11**	256.11*	52.23***
	(3.73)	(2.87)	(2.14)	(-0.32)	(1.32)	(2.79)	(2.21)	(2.75)	(0.72)	(2.09)	(2.28)	(1.75)	(6.20)
LD Dummy	-12.56**	-17.70**	3.63	-12.59	-45.72**	-20.49***	-35.70*	7.79	-24.62	-50.80	-62.16***	78.62	-18.25***
	(-2.06)	(-1.99)	(0.30)	(-1.37)	(-2.50)	(-2.71)	(-1.92)	(0.25)	(-1.17)	(-1.03)	(-2.67)	(1.01)	(-3.94)
P-value joint sign.	0.000***	0.001***	0.099*	0.374	0.017**	0.001***	0.012**	0.023**	0.329	0.065*	0.001***	0.154	0.000***
Predicted Sign	5/5	5/5	4/5	3/5	4/5	5/5	5/5	4/5	4/5	5/5	5/5	3/5	5/5
Mean Durbin Watson	1.17	1.28	1.27	1.48	1.04	1.29	1.56	1.42	1.39	0.97	1.66	1.03	
Mean Adj. R^2	0.02	0.01	0.01	0.00	0.01	0.03	0.02	0.01	0.01	0.06	0.05	0.03	0.14

The first set is designed to control for imperfections in the return data as well as to account for comovement effects with local market indices (Froot and Dabora (1999)). For instance, it might be that large return deviations of twin stocks tend to go along with of large overall market movements. To control for relative market shocks, we include the absolute log returns of both domestic market indices. Market index returns are computed in local currencies[10] and self-constructed from the value-weighted portfolio of all stocks incorporated in the respective country (see section 4.3). The advantage of using self-constructed indices is that we can exclude the twin stocks under consideration. Due to their large market capitalization, their weight within the respective stock market indices is often non-trivial. Not excluding them could result in a spurious loading on the domestic market factor. To allow for a different impact of positive and negative returns, we construct two variables for each domestic market index: $Index_{twin,t,+}$ ($Index_{twin,t,-}$) is defined as the absolute value of the log return if the signed return on the twin's domestic stock market is positive (negative) and zero otherwise. To control for currency effects, we also include the absolute change in the log exchange rate between the currencies of the countries the twins are mainly traded in. To account for the effect of different time zones in the regression with daily return frequency, we also add leads and lags as suggested by actual time differences. Specifically, for twin stock 1, which always trades in the same or an earlier time zone (see table 4.1), we include the return at t as well as t-1. For twin stock2, we include the return at t and t+1. As we have two domestic indices as well as two market states (positive and negative return) and two points of time for each index (only for the daily regressions), we have four to eight market return controls in total. For the exchange rate, we add both a lead and a lagged value in the daily regressions. For consistency, we follow this baseline approach for each DLC, irrespective of actual time lags.

The second set of control variables is intended to account for potential changes in the risk of arbitrage activities, both at the DLC level as well as at the market level. Relative mispricings can only arise in the presence of at least some limits to arbitrage. To the extent these are time-varying, they might induce changes in the impact limited investor attention can have on price discovery.

[10]Froot and Dabora (1999) argue that decomposing a foreign market's total return into the market return expressed in local currency as well as into an exchange rate component reduces measurement error induced by non-synchroneities and yields sharper insights.

Pontiff (2006) argues that idiosyncratic risk is an important impediment to arbitrage. Gagnon and Karolyi (2010) verify this by showing that the level of price parity deviations of U.S. cross-listed stocks is reliably positively related to the lagged idiosyncratic risk of a long-short strategy designed to exploit this apparent mispricing. As a very simple measure of predeterminate idiosyncratic risk at the DLC level in our setting, we use the volatility of the absolute daily return differences, measured on a rolling basis over the previous three months.[11] This implies that, compared to the univariate analysis, multivariate regressions start three months later. As a market-level proxy for the risk of arbitrage activities, we use the VIX, which is widely regarded as a forward-looking measure of overall market uncertainty. Several theories suggest that the expectation of fundamental shocks might impede arbitrageurs from trying to eliminate potential mispricings, or alternatively, that the behavior of constrained arbitrageurs themselves may amplify fundamental shocks.[12]

In sum, our multivariate regression, here at the daily level with eight market controls, can be expressed as follows:

$$|r_{1,t}-r_{2,t}|=\alpha+\sum_{k=1}^{8}\beta_k Index_k+\sum_{k=9}^{11}\beta_k Currency_k+\beta_{12}IdioVola_t+\beta_{13}VIX_t+DistractionProxySet+\epsilon_t \tag{4.6}$$

Again, we run regressions at daily and weekly frequencies, both separately for each DLC and for the pooled sample. For the weekly estimates, returns (such as market returns) are compounded. For the other control variables (such as the VIX), we use the average over the preceding five trading days. Main findings are presented in tables 4.6 and 4.7.

The main insight from these regressions is that the impact of investor distraction proxies still matters. At the daily (weekly) frequency, 55 (58) out of the in total 65 distraction coefficients obtain the predicted sign.

Estimations from the pooled regression suggest that the absolute daily (weekly) return difference is about 20 to 30 (30 to 45) basis points higher on a high distraction day (in a

[11] We have experimented with several other measures of idiosyncratic risk, such as with the volatility of signed return differences or with a return difference adjusted for comovement with domestic market indices. Inferences remain intact. See Scruggs (2007) for a detailed discussion of the role of idiosyncratic risk in the context of DLCs.

[12] See for instance Long et al. (1990), Shleifer and Vishny (1997) or Hong et al. (2011). High expected volatility as implied by high level of VIX is likely to go along with tightened funding constraints and reduced liquidity supply of speculators (e.g. Brunnermeier and Pedersen (2009), Gromb and Vayanos (2002), Nagel (2011)). Moreover, hedge funds' arbitrage ability has been documented to be reduced in times of market turbulence and high levels of VIX (e.g. Ben-David et al. (2011)). Our findings are similar if we rely on innovations of VIX instead on its raw value.

Table 4.6: Daily Return Deviations and Investor Distraction: Multivariate Tests

This table shows results from multivariate regressions of the absolute difference (in basis points) of daily currency-adjusted log returns on proxies for investor distraction as well as on several control variables, as described in detail in the text. Regressions are run separately for each DLC as well as for the pooled sample with firm-fixed effects (last column). HD/LD is short for high (low) distraction. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). *Predicted sign* denotes how many of the in total five distraction coefficients obtain the sign predicted by our hypotheses. Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Sample Start	2-Jan-91	2-Jan-91	3-Jan-94	2-Jan-91	4-Jan-93	4-Jan-93	21-Dec-95	19-Nov-96	15-Dec-97	7-Sep-98	29-Jun-01	7-Aug-01	(firm-fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)
Panel A: Distraction Proxy Set 1													
HD Proxy	1.25***	2.83***	0.48	0.77*	1.30***	1.52***	3.29***	1.47	-0.04	0.71	0.65	4.23	1.75***
	(4.32)	(5.69)	(0.85)	(1.66)	(2.68)	(3.73)	(2.92)	(1.37)	(-0.03)	(0.47)	(0.26)	(1.24)	(8.24)
P-Value	0.000***	0.000***	0.394	0.097*	0.007***	0.000***	0.004***	0.171	0.978	0.637	0.797	0.218	0.000***
Panel B: Distraction Proxy Set 2													
HD Dummy	11.09***	11.39*	9.90	0.15	6.74	7.72	33.86**	16.99	-38.01**	-7.60	40.22	80.16**	11.67***
	(3.10)	(1.94)	(1.57)	(0.03)	(1.13)	(1.52)	(2.41)	(1.43)	(-2.19)	(-0.53)	(1.08)	(2.03)	(4.51)
LD Dummy	-6.13**	-20.65***	-0.20	-6.66	-6.35	-9.10**	-7.36	3.20	-24.27*	6.79	23.00	-18.14	-9.09***
	(-2.41)	(-4.38)	(-0.04)	(-1.59)	(-1.22)	(-2.25)	(-0.81)	(0.33)	(-1.85)	(0.41)	(0.91)	(-0.57)	(-4.74)
P-value joint sign.	0.000***	0.000***	0.290	0.268	0.168	0.001***	0.033**	0.358	0.0305	0.774	0.438	0.082*	0.000***
Panel C: Distraction Proxy Set 3													
HD Dummy	11.51*	8.25	7.06	2.23	6.16	9.40	53.71**	45.86*	-18.21	-16.10	81.92	59.88	15.60***
	(1.71)	(0.80)	(0.58)	(0.27)	(0.63)	(0.84)	(2.16)	(1.70)	(-0.77)	(-0.71)	(1.35)	(0.78)	(3.26)
LD Dummy	-9.24**	-29.36***	1.24	-16.09**	0.42	-15.59***	-20.53*	-2.29	-19.38	-34.25	-36.10	-63.95	-15.04***
	(-2.34)	(-4.01)	(0.12)	(-2.47)	(0.06)	(-2.72)	(-1.74)	(-0.14)	(-0.85)	(-1.50)	(-1.05)	(-1.48)	(-5.05)
P-value joint sign.	0.014**	0.000***	0.837	0.038**	0.821	0.013**	0.024**	0.233	0.516	0.240	0.258	0.238	0.000***
Predicted Sign	5/5	5/5	4/5	5/5	4/5	5/5	5/5	4/5	2/5	2/5	4/5	5/5	5/5
Mean Durbin Watson	1.69	1.62	1.88	1.61	1.75	1.74	1.70	1.67	1.85	1.82	1.81	1.82	
Mean Adj. R^2	0.11	0.12	0.13	0.04	0.05	0.15	0.14	0.06	0.07	0.00	0.04	0.10	0.20

Table 4.7: Weekly Return Deviations and Investor Distraction: Multivariate Tests

This table shows results from multivariate regressions of the absolute difference (in basis points) of weekly currency-adjusted log returns on proxies for investor distraction as well as on several control variables, as described in detail in the text. Regressions are run separately for each DLC as well as for the pooled sample with firm-fixed effects (last column). HD/LD is short for high (low) distraction. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). *Predicted sign* denotes how many of the in total five distraction coefficients obtain the sign predicted by our hypotheses. Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Sample Start	2-Jan-91	2-Jan-91	3-Jan-94	2-Jan-91	4-Jan-93	4-Jan-93	21-Dec-95	19-Nov-96	15-Dec-97	7-Sep-98	29-Jun-01	7-Aug-01	(firm-fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)
Panel A: Distraction Proxy Set 1													
HD Proxy	2.10***	2.60***	0.77	0.32	2.05**	2.39***	3.03**	1.48	1.20	3.83	7.54***	13.48	2.46***
	(3.78)	(3.26)	(0.80)	(0.45)	(2.08)	(3.18)	(2.11)	(0.97)	(0.53)	(1.22)	(3.17)	(1.48)	(7.042)
P-Value	0.000***	0.001***	0.427	0.654	0.038**	0.001***	0.036**	0.334	0.600	0.225	0.002***	0.141	0.000***
Panel B: Distraction Proxy Set 2													
HD Dummy	21.40***	7.62	4.51	6.56	3.68	10.60	32.18*	18.54	39.16	44.49	71.08**	186.37*	18.65***
	(3.13)	(0.79)	(0.43)	(0.81)	(0.33)	(1.21)	(1.89)	(1.30)	(1.46)	(1.39)	(2.06)	(1.68)	(4.467)
LD Dummy	-6.43	-19.14**	-9.48	8.30	-25.02**	-20.32***	-5.67	1.94	15.33	-0.27	-20.60	2.93	-11.85***
	(-1.36)	(-2.38)	(-1.10)	(1.21)	(-2.44)	(-3.62)	(-0.47)	(0.12)	(0.79)	(-0.01)	(-0.87)	(0.05)	(-3.894)
P-value joint sign.	0.002***	0.014**	0.464	0.386	0.031**	0.000***	0.132	0.409	0.234	0.370	0.030**	0.247	0.000***
Panel C: Distraction Proxy Set 3													
HD Dummy	16.87*	14.47	17.19	0.95	41.43**	27.22	37.88	28.32	4.59	87.69	38.24	232.36	29.09***
	(1.67)	(1.26)	(0.90)	(0.05)	(2.06)	(1.58)	(1.13)	(1.36)	(0.20)	(1.37)	(0.84)	(0.92)	(3.745)
LD Dummy	-8.77	-24.86**	6.33	-7.09	-24.07	-20.29***	-30.37	6.19	-26.86	-17.32	-49.12**	36.23	-17.74***
	(-1.52)	(-2.50)	(0.55)	(-0.77)	(-1.44)	(-2.84)	(-1.59)	(0.21)	(-1.24)	(-0.41)	(-2.28)	(0.35)	(-3.868)
P-value joint sign.	0.080*	0.010**	0.585	0.741	0.038**	0.01***	0.155	0.397	0.455	0.358	0.056*	0.623	0.000***
Predicted Sign	5/5	5/5	4/5	4/5	5/5	5/5	5/5	3/5	4/5	5/5	5/5	3/5	5/5
Mean Durbin Watson	1.25	1.37	1.30	1.56	1.14	1.55	1.66	1.52	1.44	1.23	1.93	1.03	
Mean Adj. R^2	0.09	0.08	0.04	0.02	0.09	0.18	0.07	0.03	0.02	0.09	0.11	0.03	0.18

high distraction week) than on a low distraction day (in a low distraction week). These values correspond to about 20% to 25% of the average standard deviation of the return difference. These estimates are lower than the ones obtained for the univariate analysis. However, they remain statistically highly significant and economically meaningful.

Judging from (unreported) findings from the pooled regressions, control variables broadly take on values as predicted. Most notably, idiosyncratic volatility is strongly significant, both statistically and economically. As a rough estimate, a one standard deviation change in lagged idiosyncratic volatility is associated with a fourth standard deviation change in return deviations. This seems in line with the findings of Gagnon and Karolyi (2010) for US cross-listed stocks. The VIX is far less important, and only (slightly) significant at the weekly level. Contemporaneous domestic market returns often are significant, which appears in line with the findings of Froot and Dabora (1999) and Jong et al. (2009).

4.4.3 Deviations from Price Parity

Our focus so far has been on short-term return deviations. However, if attention constraints really mattered, than they should also cause deviations from theoretical price parity, i.e. affect the magnitude of the cumulative return discrepancy between twin stocks. In other words, as a consequence of limited attention, investors should fail to keep relative prices in line.

Table 4.8 explores this prediction. It reveals that our main findings from the return perspective indeed tend to carry over to the price perspective.

The table contrasts the level of twin stock price deviations during moments of high distraction with those during moments of low distraction. Moments of high (low) distraction are here defined as days (in panel A) or weeks (in panel B), during which the distraction proxy takes on values of 16 or greater (6 or smaller). This is a somewhat arbitrary choice. We have verified that the qualitative nature of our results does not depend on these specific breakpoints.[13]

[13]For example, see the appendix for findings when we simply use a median split, i.e. define high (low) distraction moments as days or weeks in which the proxy takes on values greater (smaller) than 11. As expected, the overall effect is slightly weaker when we rely on this less clear-cut distinction. However, basic inferences are unaffected.

Table 4.8: Deviations from Theoretical Price Parity and Investor Distraction

This table compares the level of twin stock price deviations from theoretical parity during moments of high distraction with the level of deviations during moments of low distraction. Moments of *High* (*Low*) *Distraction* are defined as days (in panel A) or weeks (in panel B) during which the distraction proxy takes on values of 16 or greater (6 or smaller). *Absolute Change* denotes the percentage point change of price deviations between times of high distraction and times of low distraction. The row below displays the corresponding p-value. To control for heteroscedasticity and autocorrelation, standard errors in both panels are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively. *Relative Change* denotes the percent change of price deviations.

ID	1	2	3	4	5	6	7	8	9	10	11	12		
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled	Pooled
Sample Start	2-Jan-91	2-Jan-91	3-Jan-94	2-Jan-91	4-Jan-93	4-Jan-93	21-Dec-95	19-Nov-96	15-Dec-97	7-Sep-98	29-Jun-01	7-Aug-01	(firm-fixed	(no fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)	effects)
Panel A: Daily Frequency														
N	1,093	1,093	432	417	644	924	612	240	150	140	120	112	5,977	5,977
High Distraction	8.49%	7.89%	8.78%	8.17%	3.79%	8.75%	4.60%	9.98%	6.86%	13.15%	7.38%	11.47%	11.45%	7.69%
Low Distraction	7.95%	6.96%	8.05%	7.93%	3.87%	8.83%	3.83%	8.86%	7.27%	10.57%	6.81%	10.92%	10.94%	7.16%
Absolute Change	0.54%	0.93%**	0.73%	0.24%	-0.07%	-0.08%	0.77%**	1.12%*	-0.41%	2.58%***	0.57%	0.55%	0.51%***	0.54%***
P-value	0.224	0.034	0.238	0.666	0.820	0.787	0.030	0.081	0.552	0.000	0.357	0.825	0.002	0.004
Relative Change	6.75%	13.43%	9.07%	3.08%	-1.86%	-0.91%	20.23%	12.67%	-5.65%	24.42%	8.43%	5.00%	4.64%	7.38%
Panel B: Weekly Frequency														
N	1,155	1,155	422	493	703	978	700	281	180	159	158	148	6,532	6,532
High Distraction	8.75%	8.17%	8.52%	8.33%	3.95%	8.90%	4.48%	9.95%	7.05%	13.21%	6.68%	12.46%	12.47%	7.83%
Low Distraction	7.63%	7.08%	8.11%	8.19%	3.94%	8.88%	3.69%	8.80%	7.27%	10.47%	6.94%	11.85%	11.84%	7.15%
Absolute Change	1.12%*	1.10%*	0.41%	0.15%	0.01%	0.02%	0.79%*	1.15%	-0.23%	2.74%***	-0.26%	0.61%	0.62%***	0.68%***
P-value	0.071	0.077	0.650	0.851	0.985	0.968	0.071	0.153	0.791	0.000	0.664	0.832	0.005	0.007
Relative Change	14.67%	15.51%	5.03%	1.78%	0.21%	0.19%	21.55%	13.05%	-3.14%	26.20%	-3.69%	5.17%	5.27%	9.49%

In line with our expectations, nine (daily analysis) or ten (weekly analysis) out of the in total twelve twin stocks exhibit higher price discrepancies in times of high as opposed to low investor distraction. While there is considerable cross-sectional heterogeneity in the absolute and relative magnitude of this effect, 24 out of the in total 28 reported differences take on the predicted sign. In the pooled regression specifications, these differences are all highly statistically significant. They are also economically meaningful. Depending on the way to compute it, the average absolute attention-driven difference in price deviations, both at the daily and the weekly frequency, is in the range of 50 to 70 basis points.[14] As a rough estimate, this corresponds to a relative increase in average price deviations of around 7% to 9% during moments of high distraction as opposed to periods of low distraction. Including the controls used in the multivariate setting in the previous section yields very similar results.

In sum, moments of limited investor attention do not only seem to go along with larger return deviations. These deviations appear systematic in the sense that they drive prices further apart from theoretical price parity.

4.4.4 Robustness Checks

Robustness across subperiods Findings are fairly stable. We have rerun all pooled multivariate regressions for each year separately. Summing up over all specifications, coefficients on distraction proxies obtain the predicted sign in more than 85%.

Alternative and additional control variables We have experimented with various modifications and extensions of our explanatory variables. For instance, we have replaced the self-constructed domestic market indices with popular broad domestic indices.[15] The pairwise correlation between the domestic indices is very high (0.9 to 0.99), and inferences remain unchanged. Moreover, we have rerun our regressions with different lead-lag speci-

[14]For instance, equal-weighting the findings for all twelve twins results in a difference of 62 (63) basis points at the daily (weekly) level. Value-weighting the twin-specific results with the number of observations yields a difference of 51 (62) basis points at the daily (weekly level).

[15]Specifically, we employed the indices also relied on by e.g. Jong et al. (2009). These indices are the ASX All Ordinaries index (Australia), the Brussels Allshare index (Belgium), the SBF 250 index (France), the Helsinki HEX index (Finland), the CBS Allshare index (Netherlands), the Stockholmboersen Allshare index (Sweden), the Swiss Performance index (Switzerland), the FTSE Allshare (UK), as well as the S&P 500 (US).

fications of return controls. The impact of the distraction proxies is persistent, no matter if one excludes all leads and lags, or if one includes a lead and a lagged value for each return variable. Furthermore, we have experimented with a variable intended to control for the absolute level of twin stock returns. The qualitative nature of our findings does not change.[16] Finally, we have explored the role of market-level illiquidity and turnover, as outlined in section 4.3. These variables are not included in the baseline multivariate regressions, as reliable and non-missing data is often not available in the early years of the sample period. The importance of the distraction proxies remains unaffected.

Impact of currency fluctuations We have rerun all univariate and multivariate tests with return differences expressed in local currencies (as opposed to a common currency as in the baseline tests). Doing so is intended to get a feeling for the impact of short-term currency fluctuations on our findings. In the overall picture, results are very similar, suggesting that currency effects only play a minor role.

Modified distraction proxies One might be concerned that our results might be driven by the specific design of our distraction proxies. This is not the case. For instance, the appendix shows findings from pooled regressions, which mirror the baseline case, but use a different weighting scheme for segment-level return shocks. Specifically, we weight each shock equally or, alternatively, with the fraction of the total domestic market capitalization the specific industry group accounts for. Inferences remain unaffected. Sensitivity checks reported in chapter 3 moreover suggest that the impact of distraction proxies remains fairly stable if one modifies its construction in several further dimensions.[17]

Inclusion of lagged return deviations We have followed the framework of Froot and Dabora (1999) in adding a lagged dependent variable on the right-hand side of the multivariate regression. This allows us to capture dynamic effects. The model assumes that the effect of attention shocks on return deviations occurs at the same day (in the same week) and then persists across future days (weeks), thereby decaying at an exponential

[16]This variable is constructed analogously to distraction proxy set 1. We first compute a raw measure as the absolute value of the sum of the twin's daily or weekly returns. Then, for each year separately, we sort these values into deciles. In the final pooled sample, the correlation between the distraction proxy decile rank and the return level decile rank is about 0.2. In the pooled multivariate regressions, the coefficient of the distraction proxy decile rank is reduced by about a tenth on average, but remains highly significant and economically meaningful.

[17]These checks include changes in the number and type of market segments, in the weighting scheme, in the model of expected returns as well as in the type of returns used.

rate. The coefficients in front of the distraction proxies can be interpreted as the short-run response of the return differential to attention shifts. The total effect can be estimated by dividing this value by (1-coefficient on lagged return differential). Main findings are presented in the appendix. As arguably expected, the immediate effect is the strongest[18], and inferences remain unchanged.

4.5 Further Insights

4.5.1 Conceptually Different Attention Proxies

Previous work has identified a number of promising proxies for investor distraction in the time series. To verify that our findings are indeed representative of a more general attention-based phenomenon, we construct four alternative distraction proxies inspired by a literature review, and then explore their explanatory power in our setup.

DellaVigna and Pollet (2009) show that the market underreacts more to earnings announcements made on Fridays. They interpret the apparent slow information diffusion as evidence for investor distraction caused by the upcoming weekend. Louis and Sun (2010) extend their analysis to the case of merger announcements. Even for these large corporate events, the market reaction on Fridays is muted, as indicated by lower abnormal trading volume and less pronounced abnormal stock returns. Louis and Sun (2010) also provide anecdotal evidence suggesting that market participants tend to be most attentive on Mondays. We thus construct a Monday (Friday) dummy as a low (high) distraction proxy.

Hirshleifer et al. (2009) argue that the number of distracting stimuli should matter. They show that the immediate (delayed) market reaction to earnings announcements is weaker (stronger) in moments where more same-day announcements compete for investors' attention. Following their line of reasoning, we rely on data from I/B/E/S to compute the daily number of earnings announcements for each stock market in our sample. As for our baseline distraction proxies, we then assign decile ranks to these values. We do so

[18] Attention shifts in period t, i.e. the difference between high and low distraction days (weeks), are roughly estimated to go along with a 20 to 25 (20 to 30) basis points increase in same period return differences.

separately for each year and for each country. For each DLC, we then define the final distraction proxy simply as the sum of the daily decile ranks of the two countries under consideration. In other words, the proxy can take on values between 2 (low distraction) and 20 (high distraction).

Karlsson et al. (2009) uncover an phenomenon they dub "ostrich effect": In down market periods, investors tend to "put their heads in the sand" and to pay less attention to their investments. Hou et al. (2009) demonstrate that this individual behavior also matters for market outcomes such as abnormal returns after corporate news. These findings motivate us to construct an investor distraction proxy, which takes on a value of one (zero) if the three months cumulative return for both stock markets under consideration is (not) negative.

For each of these distraction proxies, we mirror our baseline analysis by running pooled regressions at the daily, and, where applicable, also at the weekly level. The multivariate regressions contain the same controls as in tables 4.6 and 4.7. We exclude our baseline distraction proxies, however, to study the role of the alternative proxies in isolation.[19]

Findings are broadly consistent with a limited attention story. For each proxy, each return computation frequency, and each regression specification, the sign of the coefficients is as expected. Both their economic magnitude and statistical significance are less pronounced that the impact of our baseline distraction proxies.[20] However, despite being conceptually quite different, each distraction proxy appears to have at least some explanatory power. Together, these findings suggest that investor attention does matter.

[19]In unreported results we find that additionally including our baseline distraction proxy sets in the regressions does not change any inferences: Neither the level of their economic importance and statistical significance, nor the role of the alternative distraction proxies are materially affected. Depending on the distraction proxy set employed, the multivariate analysis suggests that combined investor attention variables can account for a daily return deviation between 35 and 45 basis points. These values correspond to slightly more than 30% to slightly more than 40% of the average standard deviation of daily return deviations.

[20]Results for the proxy based on I/B/E/Sdata are similar if we focus on earnings announcement after 1994 to assure data quality, as suggested by DellaVigna and Pollet (2009).

Table 4.9: The Impact of Alternative Investor Distraction Proxies

This table shows results from pooled regressions of twin stock return deviations on alternative proxies for investor distraction as well as on several control variables, as described in detail in the text. Return deviations are computed as the absolute value of the difference between the currency-adjusted daily or weekly log returns of the twins. In panel A, the distraction proxy is computed as the sum of two country-specific distraction proxy decile ranks, as obtained from yearly sorts of the number of daily earnings announcements in the stock market under consideration. In panel B, the distraction proxy is computed as a dummy variable which takes on a value of of one (zero) if the three months cumulative domestic market return for both countries under consideration is (not) negative. In panel C (D), the distraction proxy is a dummy variable which takes on a value of one on Fridays (Mondays) and zero otherwise. All regressions contain firm-fixed effects. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

	Panel A: Competing events (Prediction: positive sign)			
Frequency	Daily	Daily	Weekly	Weekly
Regression framework	Univariate	Multivariate	Univariate	Multivariate
Coefficient	0.53***	0.36**	0.07	0.59**
t-value	(2.78)	(2.17)	(0.25)	(2.07)
p-Value	0.006	0.030	0.803	0.038
Adj. R^2	0.12	0.19	0.13	0.17
	Panel B: Down market periods (Prediction: positive sign)			
Frequency	Daily	Daily	Weekly	Weekly
Regression framework	Univariate	Multivariate	Univariate	Multivariate
Coefficient	26.99***	3.98	24.25***	5.80
t-value	(8.64)	(1.40)	(5.53)	(1.38)
p-Value	0.000	0.161	0.000	0.168
Adj. R^2	0.13	0.19	0.14	0.17
	Panel C: Fridays (Prediction: positive sign)			
Frequency	Daily	Daily		
Regression framework	Univariate	Multivariate		
Coefficient	3.61*	2.81		
t-value	(1.90)	(1.48)		
p-Value	0.057	0.138		
Adj. R^2	0.12	0.19		
	Panel D: Mondays (Prediction: negative sign)			
Frequency	Daily	Daily		
Regression framework	Univariate	Multivariate		
Coefficient	-4.69**	-6.61***		
t-value	(-2.51)	(-3.66)		
p-Value	0.012	0.000		
Adj. R^2	0.12	0.19		

4.5.2 Evidence from Dual-Class Shares

One might be concerned that our findings and its implications are limited to the special case of twin stocks. Moreover, data imperfections such as time lags or currency fluctuations might still matter to a certain extent. To address these concerns, we evaluate our line of reasoning out of sample in a related setting. We explore the role of investor attention for return deviations of US dual-class shares. Dual-class shares represent two classes of common stock issued by the same company. They both have equal cash flow rights, but differ in their voting rights. As we only consider US stocks, time and currency differences do not matter here.

However, in contrast to the twin stocks we have studied so far, returns and prices of dual-class shares might well differ for rational reasons (e.g. Zingales (1995)). There might be pronounced differences in liquidity between both classes of stock. Moreover, voting shares might contain a potentially time-varying premium due to the value of the voting rights. However, for several reasons, these factors are unlikely to materially affect our analysis. First, Schultz and Shive (2010) show that price deviations between dual-class shares are widely fluctuating, whereas the value of liquidity and voting rights should be rather stable on a day-to-day basis. Simple trading strategies designed to exploit temporary price deviations yield abnormal returns, which would hardly be generated if prices diverged for rational reasons. Using intraday TAQ data, the authors are able reveal that price pressure or slow information diffusion often cause price to differ, leading to clear mispricings. We hypothesize that limited investor attention might provide a partial explanation for this phenomenon. Second, we apply a strict screening procedure to assure that only very liquid stocks enter the following tests.[21] Our initial sample consists of all 100 pairs of dual-class shares studied in Schultz and Shive (2010). In the final sample, we are left with 18,676 eligible daily observations of 23 pairs over the sample period from January 1993 to December 2008. Third, in an attempt to control for the potentially time-varying value

[21] We only consider observations which meet the following four requirements. First, both stocks belong to NYSE market capitalization decile 4 or larger. Second, the daily trading volume for each stock is at least one million dollar. Third, a daily illiquidity ratio, computed as absolute daily return divided by trading volume in million dollars, is less than 0.01. Fourth, there are at least 50 eligible observations for each pair. To reduce the effect of outliers, we finally discard daily return differences greater than the 99.9 percentile. Averaged across all observations in the final sample, the median stock has a market capitalization of close to three billion dollar and a daily trading volume of close to 15 million dollar. The qualitative nature of our findings is very robust with respect to modified screening procedures. Inferences are also unaffected if we rely on the initial sample without any screenings.

contained in the extra votes, we have discarded all days or weeks for which we could gather news articles from the Dow Jones News Service.[22] This procedure is intended to identify potentially relevant events such as annual meetings. In unreported tests, we verify that our findings remain qualitatively unchanged. Moreover, Schultz and Shive (2010) find that the exclusion of such events hardly affects the profitability of their trading strategy.

To assure consistency and comparability, our tests follow the pooled analysis for twin stocks to the extent possible. We start by constructing daily and weekly return deviations for dual-class shares. At the daily (weekly) frequency, the average difference is 0.57% (0.83%) with a standard deviation of 0.69% (1.07%). We then regress them on proxies for US investor distraction as well as on a number of controls. The investor distraction proxy consists of the decile distraction rank or, alternatively, of two dummy variables. The latter take on a value of one in the case of high (low) distraction days or weeks, as indicated by distraction decile 10 (1). We consider two multivariate specifications. The first includes the US market return, idiosyncratic risk, as well as the VIX. This set is roughly comparable to the multivariate baseline analysis for twin stocks. The second specification additionally includes several further firm-level and market-level controls.[23].

Main findings from various regressions are presented in table 4.10. They turn out to be very similar to the ones obtained for twin stocks. Univariate regressions suggest that the absolute daily (weekly) return difference is about 15 to 20 (20 to 30) basis points higher on a high distraction day (in a high distraction week) than on a low distraction day (in a low distraction week). These values correspond to about 20% to 30% of the average standard deviation of the return difference. Multivariate findings are about a third smaller, but remain highly significant. In sum, results are broadly in line with our expectations.

[22] Due to its comprehensive coverage, this database has widely been relied on in previous studies, and argued to be "the best approximation of public news for traders" (Chan (2003), p. 230).

[23] We here use the differences in NYSE market capitalization decile, in dollar trading volume, as well as in the illiquidity ratio as firm controls. We use the Fama and French (1993) factors as well as the momentum and the short-term reversal factor as market controls. We have experimented with further controls, which however did not affect any inferences.

Table 4.10: Return Deviations of US Dual-Class Shares and Investor Distraction

This table shows results from pooled regressions of return deviations of US dual-class shares on proxies for investor distraction as well as on several control variables. Return deviations are computed as the absolute value (in basis points) of the difference between the daily or weekly log returns of dual-class shares. All regressions are run with firm-fixed effects. The sample period spans January 1993 to December 2008, and includes 23 pairs of dual-class shares in total. HD/LD is short for high (low) distraction. The high (low) distraction dummy is 0 if the US distraction proxy takes on a decile rank of 10 (1), and zero otherwise. The controls in $Multivariate$ 1 are the idiosyncratic risk of the pair, the VIX, and the US market return. *Multivariate* 2 includes additional firm-level and market-level controls, as described in detail in the text. In the last row, *Predicted sign* denotes how many of the in total three distraction coefficients obtain the predicted sign. In panel B, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

Frequency	Daily	Daily	Daily	Weekly	Weekly	Weekly
Regression framework	Univariate	Multivariate I	Multivariate II	Univariate	Multivariate I	Multivariate II
N	18,657	18,486	18,486	18,631	18,468	18,468
Panel A: Distraction Proxy Set 1 (Distraction Proxy Decile Rank)						
HD Proxy	1.63***	1.25***	1.15***	2.40***	1.85***	1.61***
	(8.37)	(7.30)	(6.71)	(6.29)	(5.63)	(4.80)
P-Value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Adj. R^2	0.17	0.25	0.27	0.21	0.30	0.30
Panel B: Distraction Proxy Set 2 (High and Low Distraction Dummies)						
HD Dummy	11.76***	8.71***	8.00***	20.96***	14.56***	12.72***
	(5.84)	(4.75)	(4.34)	(5.49)	(4.4.0)	(3.85)
LD Dummy	-6.48***	-5.67***	-5.35***	-8.78***	-9.68***	-8.85***
	(-4.66)	(-4.26)	(-4.05)	(-2.97)	(-3.56)	(-3.24)
P-value joint sign.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Adj. R^2	0.17	0.25	0.27	0.21	0.30	0.30
Predicted Sign	3/3	3/3	3/3	3/3	3/3	3/3

4.6 Conclusion

We believe that, due to their special nature, twin stocks present a unique opportunity to study the importance of investor attention shifts for price discovery. First, in contrast to most other settings, twins' fundamentals are identical. In other words, no model of intrinsic value is required. This overcomes the bad model problem inherent in many asset pricing tests. Second, previous research has shown that arbitrage is limited in these cases. Thus, potentially arising mispricings are less likely to be quickly eliminated and consequences of not fully rational investor behavior can easier be detected in equilibrium outcomes. Third, findings suggestive of a non-trivial role of limited attention could be considered a conservative estimate for the impact attention constraints might potentially have on asset pricing and market efficiency. Arguably, economic links between securities in financial markets are often more less explicit and less transparent, and might thus be more prone to mispricings induced by limited investor attention.

This chapter lends support to the idea that attention shifts can help to explain why returns of twin stocks become temporarily delinked, thereby inducing or amplifying violations of the law of one price. Clearly, highlighting the role of attention constraints alone is by far not enough to satisfactorily explain the puzzling behavior of these stocks. However, our approach might provide some directions for future research, as a gap in the literature appears to exist. Previous work on DLCs has mainly elaborated on why mispricings can persist, but offers little guidance on why twin stock returns diverge in the first place.

Chapter 5

How Should Private Investors Diversify? - An Empirical Evaluation of Alternative Asset Allocation Policies to Construct a “World Market Portfolio”

5.1 Introduction

Despite the recognized benefits of diversification as “the only free lunch in investment”, private investors seem to sometimes violate even its basic principles. In fact, “these discrepancies, or investment mistakes, are central to the field of household finance.” (Campbell (2006, p. 1554)). In this chapter, we thus aim to derive easily implementable asset allocation guidelines for individual investors. Our approach allows us to evaluate numerous competing policies for the construction of a “world market portfolio”. Specifically, we ask the following questions: From the perspective of private investors in real-life situations, what is the most promising way to diversify? Do simple rules of thumb already provide a powerful remedy against widespread investment biases? Which heuristics are particularly able to realize diversification potential? To what extent do these strategies underperform when benchmarked against sophisticated optimization models?

Empirical studies provide extensive evidence of private investors making portfolio choices that are difficult to reconcile with standard financial theory. As such, households often fail to participate in the stock market at all (see, e.g., Campbell (2006) and Kimball and Shumway (2010)). Given the size of the equity premium over the past, the welfare costs of this behavior are likely to be high. Among those households that do invest in equities, many studies document further costly mistakes. First, individuals tend to prefer domestic over foreign investments thereby forgoing the benefits of international diversification (see French and Poterba (1991), Grinblatt and Keloharju (2001) and Kilka and Weber (2000)). Second, many households own relatively few individual stocks which may cause a significant exposure to idiosyncratic risk (see, e.g., Goetzmann and Kumar (2008) and Polkovnichenko (2005)). Third, data from online brokerage accounts show that many individuals are overconfident and trade too much (see Odean (1999) and Barber and Odean (2000)). Puzzling investment behavior carries over to diversification over asset classes. Analyzing a large sample of retirement accounts, Agnew et al. (2003) show that most asset allocations are extreme (either 100 percent or zero percent in equities) and there is inertia in asset allocations. Tang et al. (2010) conclude that most participants make inefficient portfolio investment choices in retirement plans. The failure of diversifying adequately over asset classes must be considered as particularly problematic as asset allocation has been shown to be the main determinant of portfolio performance (see e.g., Brinson et al. (1986) or Ibbotson and Kaplan (2000)). Additionally, recent findings on the correlation structure of international stock markets imply that even worldwide equity market diversification can offer only limited benefits. First, increasing return correlations within the stock universe over the last decades (Goetzmann et al. (2005)) lead to decreasing diversification gains (Driessen and Laeven (2007)). Second, correlations tend to be particularly high in periods of poor performance (see e.g. Longin and Solnik (2001)). Thus, benefits from global diversification in the stock market tend to be smallest when they are most needed.

To sum up, risk-adjusted portfolios of most private households underperform even standard domestic stock market indices at a signicant margin, and thus leave substantial room for improvement. But how should private investors diversify? While academic research almost exclusively relies on the performance of various extensions of the Markowitz

(1952) framework, we also concentrate on the relative investment value of heuristic diversification strategies. This is particularly relevant for private investors as most individuals will not have the knowledge and resources to implement sophisticated extensions of the Markowitz model. In addition, Markowitz approaches, while being optimal in theory, suffer from estimation error in expected returns, variances and covariances when implemented in practice. There is a large literature explicitly dealing with how to improve the out-of-sample performance of these strategies - with partly disillusioning results. Recent studies focussing primarily on U.S. stock portfolios show that the estimation error is so severe that various optimization models are oftentimes unable to beat a naive 1/N diversification strategy (see, e.g. DeMiguel et al. (2009b), Tu and Zhou (2011), and Duchin and Levy (2009)). Hence, it seems insufficient to limit the analysis to these models.[1] In the empirical analysis, we thus analyze the performance of eleven well-established or recently proposed extensions of the Markowitz framework as opposed to a broad range of plausible heuristics. In doing so, we combine two prominent ways of diversification that are usually analyzed separately: International diversification in the stock market and diversification over different asset classes. To achieve comparability with the previous literature, the following two-step procedure is employed.

First, we concentrate on global diversification in the stock market. Such an analysis might be considered a complement of the influential study of DeMiguel et al. (2009b). In addition, we provide an out-of-sample test of the norm-constrained allocation strategies which have been proposed recently in DeMiguel et al. (2009a). In their empirical analysis, the authors are able to show that this novel class of models often outperforms existing portfolio-strategies at a significant margin. We rely on the bootstrap technique developed in Ledoit and Wolf (2008) to assess the significance of differences in Sharpe ratios. In contrast to the standard test statistic of Jobson and Korkie (1981), its validity is not sensitive to the underlying distribution and thus particularly suitable for the analysis of financial time-series data. The approach is designed to provide reliable inference even when returns exhibit fat tails or show typical time-series characteristics such as volatility clustering or autocorrelation. With regard to performance evaluation, we gain additional insights

[1] The out-of sample performance of an equally weighted portfolio as compared to the performance of the standard Markowitz approach is in fact a longstanding and controversial debate in portfolio optimization. Early discussions include, for instance, Frankfurter et al. (1971), Brown (1979), or Jobson and Korkie (1981). For a recent study arguing that optimized portfolios do outperform equally weighted portfolios, see Kritzman et al. (2010).

by building on factor models borrowed from the mutual fund literature. We construct a global Carhart (1997) four-factor model using Datastream's stock universe. This allows us to draw inferences which are not seen from an analysis of traditional performance measures alone.

Second, we extend our analysis to the multi-asset class case incorporating bonds and commodities. In the baseline scenario, we derive simple fixed-weight policies from the academic as well as practitioner literature and compare them to the optimization models. Again, we employ a multi-factor regression framework to identify the underlying drivers of performance. To this end, we construct value and momentum factors for bonds and commodities building on recent work of Asness et al. (2009). Our approach adds to the literature on performance attribution of multi-asset class portfolios. Finally, we analyze the performance of more than 5,000 alternative fixed-weight strategies covering every possible proportion of the asset classes in 1% steps. This enables us to gain deeper insights into the structural composition of promising portfolios.

We find that none of the Markowitz-based portfolio models is able to significantly outperform simple heuristics out-of-sample. This holds for both international equity diversification and for the asset allocation case. Instead almost any well-balanced fixed-weight proportion of stocks, bonds and commodities is able to realize considerable diversification gains. A number of sensitivity checks assures the robustness of our results. We thus suggest a simple and cost-efficient asset allocation approach for private investors.

The remainder of this chapter is organized as follows. Section 5.2 describes our data. Section 5.3 discusses popular extensions of the Markowitz approach, leading to the selection of promising optimization models for the construction of a "world market portfolio". Subsequently, we derive alternative heuristic asset allocation policies. Section 5.4 contains the empirical analysis. A summary of the results is given in section 5.5.

5.2 Data and Descriptive Statistics

5.2.1 Asset Classes and Data

Given our focus, we pay particular attention to the practicability of our results. We therefore base our study on renowned indices, which are investable for private investors at low costs via exchange-traded funds. We concentrate on Euro-Zone private investors within a yearly rebalanced buy-and-hold approach.[2] We incorporate stocks, bonds as well as commodities in the analysis. These asset classes are represented by indices whose selection is based on the criteria transparency, representativeness, investability, liquidity and data availability.[3]

Based on these requirements, we rely on the Morgan Stanley Capital International (MSCI) index family, which has been widely used in previous studies (e.g., Driessen and Laeven (2007), De Roon et al. (2001)), to cover the global stock universe. In the baseline analysis, stocks in the "world market portfolio" are represented by the four regional indices MSCI Europe, MSCI North America, MSCI Pacific as well as MSCI Emerging Markets. Taken together, they currently cover 45 countries and track the performance of several thousand stocks. The MSCI indices are designed to cover 85% of the free float-adjusted market capitalization of the respective investable equity universe.

Bonds are incorporated because of their low correlation with stocks. In the baseline analysis, they are represented by the iBoxx Euro Overall index, which consists of Euro-Zone bonds of different maturities and credit ratings.[4] The index currently tracks the perfor-

[2]Our motivation to focus on Euro-Zone investors is twofold. First, many studies takting the special viewpoint of US (stock) investors find the additional benefit from investing abroad to be economically small (e.g. De Roon et al. (2001), Driessen and Laeven (2007)). Non-US perspectives have received far less attention so far. Second, hardly any of the financial products available to Euro-Zone private investors satisfies our requirements of a transparent, cost-efficient and broadly diversified portfolio. On the one hand, there are passive products which are based on pure stock, bond or commodity indices. Even within the respective asset class, they are often not comprehensively diversified. On the other hand, there are actively managed multi-asset class funds. However, actively managed funds on average underperform passive benchmarks after costs (e.g., Fama and French (2010) and Comer et al. (2009)).

[3]We require the index composition and index rules to be disclosed by the index provider (transparency). The index should already cover most of the market within an asset category to reduce complexity (representativeness). In doing so, the "world market portfolio" can be constructed with only few highly diversified indices. Moreover, low-cost exchange-traded funds tracking these indices should exist to enable private investors to actually implement our suggestions (investability and liquidity). Finally, we require a long return data history to conduct powerful statistical tests (data availability).

[4]As we aim to derive suggestions for private investors, we do not consider currency hedging. For internationally diversified

mance of more than 2,200 bonds. In robustness checks, we also make use of the iBoxx Euro Sovereign Index, which only consists of government bonds, the JPM Global Bond Index, and the ML European Monetary Union Index.

Partly due to a lack of investability, commodities have long been neglected by private investors. However, many studies provide evidence of the high diversification potential of broad-based commodity futures indices.[5] Furthermore, diversification benefits tend to be especially pronounced in times of unexpected inflation and declining stock markets. In the baseline analysis, commodities are represented by the S&P GSCI Commodity Total Return Index. This world-production weighted index currently includes 24 commodity futures contracts that track the performance of energy products, industrial and precious metals, agricultural products and livestock. In sensitivity checks, commodities are also represented by the Reuters/Jefferies Total Return Index and the DB Commodity Euro Index, respectively.

We do not incorporate real estate in our analysis as individual investors are often already heavily exposed to real estate risk (e.g., Calvet et al. (2007), Campbell (2006)). Thus, the additional inclusion of real estate in the overall portfolio might lead to a lack of diversification. Moreover, we do not consider alternative asset classes such as hedge funds and private equity for two reasons. First, their diversification potential in the multi asset case is often found to be limited (e.g., Amin and Kat (2003), Ennis and Sebastian (2005), Patton (2009) and Phalippou and Gottschalg (2009)). Second, we could not identify indices satisfactorily meeting our selection criteria.

Our evaluation period starts in February 1973 and ends in December 2009, thus extending previous studies on international diversification in the stock market (e.g., Driessen and Laeven (2007), De Roon et al. (2001) or De Santis and Gerard (1997)). For all indices, we use Euro-denominated total return indices extracted from Thomson Reuters Datastream.

---

bond portfolios, Black and Litterman (1992) and Eun and Resnick (1994) find that currency risk needs to be controlled for. We thus restrict our analysis to Euro-denominated bonds. As the iBoxx index universe is only available from 1999 on, we replace the return of the iBoxx Euro Overall Index with the return of the REXP for the time period before 1999. Our approach is justified by a monthly return correlation of 0.965 between these two indices after 1999.

[5] Historically, these indices delivered equity-like returns and volatilities. At the same time, they provided low and partly even negative correlations with stocks and bonds (e.g., Erb and Harvey (2006) and section 5.2.2). Other commodity exposure such as physical trading, individual commodity futures or stocks of companies owning and producing commodities does not offer the specific risk, return, and correlation features of broad-based commodity futures indices (e.g., Erb and Harvey (2006) and Gorton and Rouwenhorst (2006)). Thus, they are less suitable for our analysis.

Hence, our findings refer to an investment without currency hedging, which is a realistic assumption for private investors.[6]

To implement our heuristic portfolio strategies in the stock universe, we require the gross domestic product (GDP, in current U.S. dollars) and the stock market capitalization of the MSCI index regions. We obtain these data from the World Bank, the International Monetary Fund (IMF) and Thomson Reuters Datastream, respectively. We use the three month FIBOR as a proxy for the risk-free asset. Historical stock market capitalization data is available from 1973 on, which marks the lower bound of our evaluation period.

5.2.2 Descriptive Statistics

Table 5.1 gives an overview of the monthly return parameters of the asset classes which are represented by the iBoxx Euro Overall index, the S&P GSCI Commodity Total Return index and a number of stock indices. The latter comprise the four regional MSCI indices as well as a global capitalization-weighted stock index constructed from the four regional indices. The MSCI Emerging Markets are only incorporated from 1988 on, as this is the starting point of the index calculation.[7] Table 5.1 shows only small differences in the average monthly Sharpe ratio of the regional stock indices (0.091) compared to the global stock index (0.098). Over the last 20 years, this difference vanishes completely. This result motivates, first, the analysis of alternative allocation mechanisms for the stock market and, second, the incorporation of additional asset classes.

To assess the diversification potential of a "world market portfolio", Figure 5.1 and Figure 5.2 illustrate the time-series behavior of correlations within the stock markets and across asset classes, respectively. Correlation coefficients are computed using a rolling window approach based on the previous 60 months.

Figure 5.1 reveals an almost steady increase in the comovement of international stock mar-

[6] To convert index levels in Euro we refer to the time series of synthetical Euro/USD exchange rates as calculated by Thomson Reuters Datastream. In robustness checks, we redo the analysis using the historical DEM/USD exchange rate as published by Deutsche Bundesbank. The qualitative nature of our results does not change.

[7] Driessen and Laeven (2007) emphasize that investment restrictions were imposed on many emerging markets till the mid 80s and that reliable index calculations have only been available since then. Thus, the return of our global stock index can be considered a proxy for the performance of worldwide investable equity.

Table 5.1: Descriptive Statistics for the Different Indices

This table reports the return distribution of the various indices which we consider for portfolio construction. Returns are calculated using Datastream's total return index (code: RI) and denominated in Euro. Global Stock Index is a market-weighted stock index comprising the four different regional stock indices MSCI Europe, MSCI North America, MSCI Pacific, and MSCI Emerging Markets.

Asset Class/ Region	Sample Period	Sharpe Ratio	Mean Return	Std. Dev. Return	VaR 95%
Stocks: Regional Indices					
Emerging Markets	88-09	0.122	1.29%	7.45%	-12.13%
Europe	73-09	0.116	1.01%	4.86%	-7.75%
North America	73-09	0.093	0.95%	5.39%	-8.11%
Pacific	73-09	0.065	0.83%	5.91%	-8.61%
Average	**73-09**	**0.091**	**0.93%**	**5.39%**	**-8.16%**
Average	**88-09**	**0.072**	**0.82%**	**5.88%**	**-9.57%**
Global Stock Index	**73-09**	**0.098**	**0.92%**	**4.79%**	**-8.44%**
Global Stock Index	**88-09**	**0.060**	**0.68%**	**4.92%**	**-8.73%**
Other Asset Classes					
Bonds	73-09	0.108	0.57%	1.12%	-1.27%
Commodities	73-09	0.076	0.92%	6.28%	-9.65%

kets since the 1980's. However, as Figure 5.2 illustrates, there is no (in the case of bonds) or at best weak (in the case of commodities) evidence of an increase in correlations across asset classes. Nevertheless, correlations vary considerably through time, which points to potential estimation errors in Markowitz-based optimization methods (see section 5.3.1). We discuss promising optimization approaches in the next section.

5.3 Asset Allocation Models

The models considered for portfolio selection in the case of both global stock market diversification and diversification over asset classes are briefly summarized in Table 5.2. The last column of this table gives the abbreviation that we use to refer to the model in

Figure 5.1: Time Series Behavior of Correlations within the Stock Market

This figure depicts the movement in the average correlation over the sample period for the regional stock indices MSCI Europe, MSCI North America, MSCI Pacific and MSCI Emerging Markets with respect to all other stock indices. Correlation coefficients are computed using a rolling window approach based on the previous 60 months.

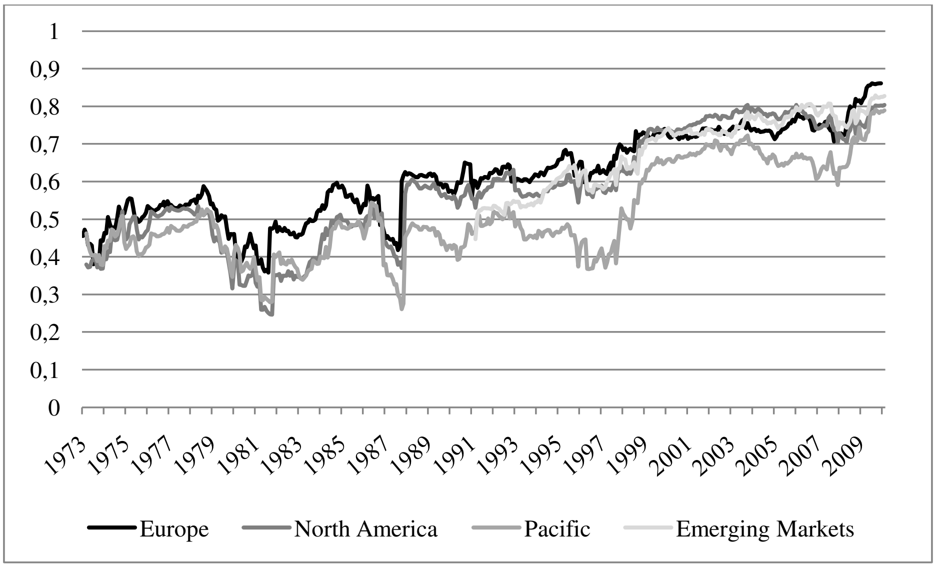
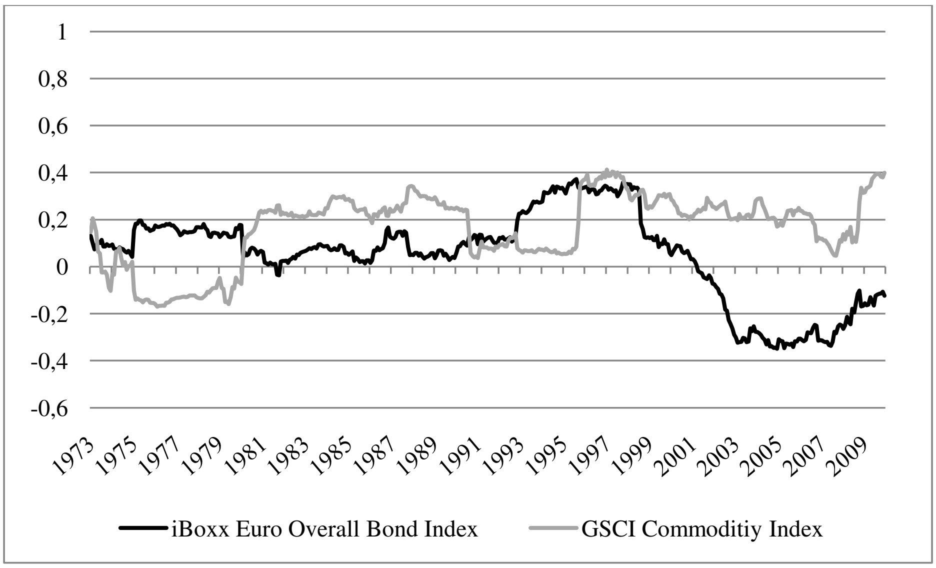


Figure 5.2: Time Series Behavior of Correlations between Asset Classes

This figure depicts the movement in the average correlation over the sample period for the iBoxx Euro Overall Index and the S&P GSCI Commodity Total Return Index with respect to the regional MSCI stock indices. Correlation coefficients are computed using a rolling window approach based on the previous 60 months.



the results section.

5.3.1 Markowitz-Based Optimization Models

We use a variety of model extensions that have been suggested in the existing literature to deal with the well-known problem of estimation error, which is ignored in the traditional mean-variance model of Markowitz (1952).[8] These models either impose additional constraints in the optimization process, shrink the estimated input parameters in order to mitigate the impact of estimation error, or both. Shortsale constraints prevent the optimization model from taking extreme long and short positions to exploit even small differences in the return structure of assets. Shrinkage models correct the estimated parameters toward a common value. In doing so, they aim at reducing the error-maximizing property of the mean-variance model when historical data is used for parameter estimation (e.g., Jorion (1985)). As shown by Jagannathan and Ma (2003), both approaches work similarly by increasing the number of assets with non-negative portfolio weights which enforces a certain extent of diversification.

The first model we implement is the mean-variance framework with non-negativity condition ($maxsr$). The objective of this model is to maximize the Sharpe ratio of the portfolio, which allows us to refrain from considering individual risk preferences in the optimization process. In addition, we employ three extensions of this model that either shrink the sample means ($js - maxsr$), the sample variance-covariance matrix ($ccm - maxsr$), or both ($js - ccm$). The shrinkage estimation of expected returns is based on the work of James and Stein (1961). In our study, we use the estimator proposed by Michaud (1998). We shrink the elements of the variance-covariance matrix employing the constant correlation model developed in Ledoit and Wolf (2004).[9]

In addition to models which try to maximize the Sharpe ratio, we employ several models which aim at constructing minimum variance portfolios. The superior performance

[8]Consistent with previous empirical evidence, the traditional mean-variance optimization without constraints leads to extreme long and short positions with exorbitant high turnover. Therefore, we refrain from reporting these results.

[9]The authors provide the code on their web-site (http://www.ledoit.net/shrinkCorr.m). We assume a constant correlation equal to the historical correlation average for the stock market indices and a correlation of 0 between different asset classes. Our results are unchanged if we simply use the historical correlation average over all indices irrespective of the asset class underlying the index.

Table 5.2: List of Portfolio Models

This table lists the various Markowitz-based optimization models from the existing literature (Panel A) and heuristic models (Panel B) which we consider for portfolio construction. δ is the threshold parameter developed in DeMiguel et al. (2009a) to limit the norm of the portfolio weight vector. The last column gives the abbreviation that we use to refer to the model.

No.	Portfolio Model	Abbreviation
	Panel A: Markowitz-based portfolio optimization models from the existing literature	
1	Maximum Sharpe ratio approach with shortsale constraints	maxsr
2	Minimum variance approach without shortsale constraints	minvar-nb
3	Minimum variance approach with shortsale constraints	minvar
4	James/Stein estimator of expected returns with shortsale constraints	js
5	James/Stein estimator of expected returns plus Ledoit/Wolf constant correlation model with shortsale constraints	js-ccm
6	Maximum Sharpe ratio approach plus Ledoit/Wolf constant correlation model with shortsale constraints	ccm-maxsr
7	Minimum variance approach plus Ledoit/Wolf constant correlation model with shortsale constraints	ccm-minvar
8	1-norm constrained minimum variance portfolio with δ calibrated using cross-validation over portfolio variance	nc1v
9	1-norm constrained minimum variance portfolio with δ calibrated by maximizing portfolio return in previous period	nc1r
10	2-norm constrained minimum variance portfolio with δ calibrated using cross-validation over portfolio variance	nc2v
11	2-norm constrained minimum variance portfolio with δ calibrated by maximizing portfolio return in previous period	nc2r
	Panel B: Heuristic portfolio models considered in this paper	
12	GDP-weighted stock portfolio	gdp
13	Market-weighted stock portfolio	macap
14	Equally-weighted stock portfolio	naiv
15	Asset Allocation Model with the following weights: 60% stocks, 25% bonds and 15% commodities; stock portfolio is GDP-weighted	60-25-15; gdp
16	Asset Allocation Model with the following weights: 60% stocks, 25% bonds and 15% commodities; stock portfolio is market-weighted	60-25-15; macap
17	Asset Allocation Model with the following weights: 60% stocks, 25% bonds and 15% commodities; stock portfolio is equally-weighted	60-25-15; naiv

of minimum variance optimization, in particular compared to models that do not ignore information about sample mean returns, has been demonstrated in various studies (see, e.g., Haugen and Baker (1991), Chopra et al. (1993), and Jagannathan and Ma (2003)). We implement the traditional minimum variance approach with and without short-sale constraints ($minvar$, $minvar - nb$), the minimum variance approach with shrinkage estimation of the variance-covariance matrix using the constant correlation model and short-sale restriction ($ccm - minvar$), and a set of extensions to the general minimum variance framework ($nc1v, nc1r, nc2v, nc2r$) which have recently been developed by DeMiguel et al. (2009a). In their empirical analysis, the authors are able to show that this novel class of models often outperforms existing portfolio strategies at a significant margin. They impose the additional constraint that the sum of the absolute values of the portfolio weights (known as 1-norm) or the sum of the squared values of the portfolio weights (known as 2-norm) must be smaller than a given parameter threshold δ. Effectively, this constraint allows portfolios to have some short positions, but restricts the total amount of short-selling. In order to calibrate the value of the threshold parameter δ, DeMiguel et al. (2009a) use two different methods. First, they choose the parameter δ which minimizes the portfolio variance if the sample is cross-validated. Second, they set δ to maximize the portfolio return in the last period in order to exploit positive autocorrelation in portfolio returns.[10]

Overall, we believe to use a promising set of scientific portfolio choice models against which we test the heuristic construction rules, which are illustrated in the next subsection.

5.3.2 Heuristic Models

5.3.2.1 International Stock Market Diversification

We consider three different weighting schemes for a global stock portfolio: Equal-weighting (1/N heuristic), market value-weighting and GDP-weighting.

An equally-weighted portfolio might be considered a natural benchmark for more sophis-

[10] For further information about the derivation of the portfolio models and the motivation of DeMiguel et al. (2009a), we refer the reader to their study. We do not evaluate other portfolio models considered in their paper, because the design of these models is very similar to the ones tested in our study and all models achieve very similar results in terms of out-of-sample portfolio variance, Sharpe ratio and turnover.

ticated methods of portfolio optimization. Firstly, it is very easy to implement. And, secondly, private investors have been shown to often rely on this naive allocation rule (e.g., Benartzi and Thaler (2007)).

Another strategy is to base portfolio weights on the relative market capitalization of the constituents. This concept is at the heart of most major stock market indices and thus easy to follow for private investors. Liquidity and investment capacity arguments are important benefits of these indices, though of minor relevance for our objective. However, an undisputed advantage of this approach is its very low turnover as portfolio weights automatically rebalance when security prices fluctuate.

Nevertheless, concerns against this weighting scheme have recently been raised. Figure 5.3 gives the intuition behind these arguments. It shows the time series of portfolio weights of a market-value weighted stock index constructed from the MSCI indices for North America, Europe, the Pacific region and the Emerging Markets. Figure 5.3 illustrates that the resulting global stock index tends to be dominated by single regions. Between 1998 and 2007, for example, the weight of North America was on average about 45%. As the MSCI indices themselves are cap-weighted, US large caps substantially drove the performance of the global stock universe during that period. In contrast, the portfolio weights in the previous decade were heavily influenced by the bull and subsequent bear market of the Japanese stock market. The fraction of the Japan-dominated Pacific region was more than 52% in 1989 and heavily dropped to about 15% in 1998. These examples illustrate the pro-cyclical nature of value-weighted indices.

Motivated by many studies arguing that price fluctuations sometimes do not fully reflect changes in company fundamentals (e.g., Shiller (1981)), a growing literature questions the efficiency of value-weighted indices (e.g., Treynor (2005), Siegel (2006)). Recently, alternative index concepts aimed at better approximating true firm values have been proposed. These indices are often weighted by fundamental measures such as earnings, dividends or book values (Arnott et al. (2005)), building on the intuition that this scheme might be less volatile and less driven by sentiment. Consistent with this rationale, back-testing shows that fundamentally-weighted country-specific indices have outperformed standard value-weighted indices in the past (e.g., Arnott et al. (2005)).

These findings justify the inclusion of a fundamentally-oriented global stock market index

Figure 5.3: Time Series Evolution of Portfolio Weights of a Cap-Weighted Stock Index

This figure depicts the portfolio weights of a market-value weighted stock index constructed from the MSCI indices for North America, Europe, the Pacific region and the Emerging Markets over the sample period. The data source is Thomson Reuters Datastream.

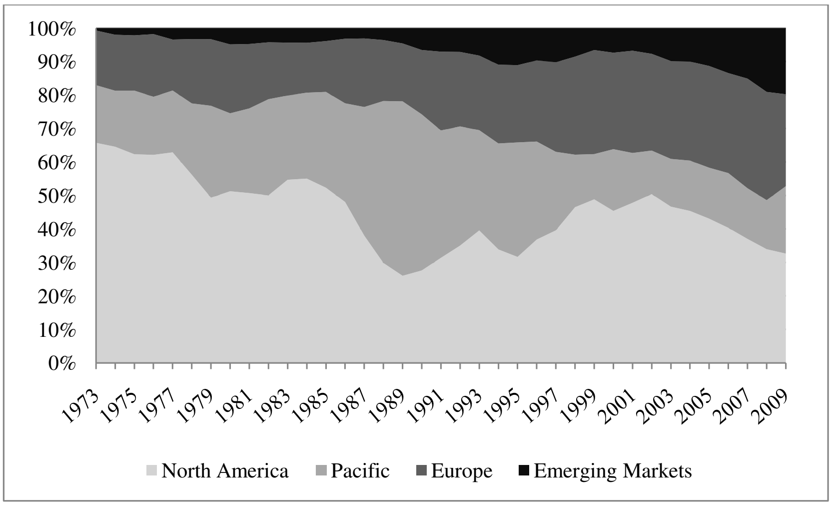
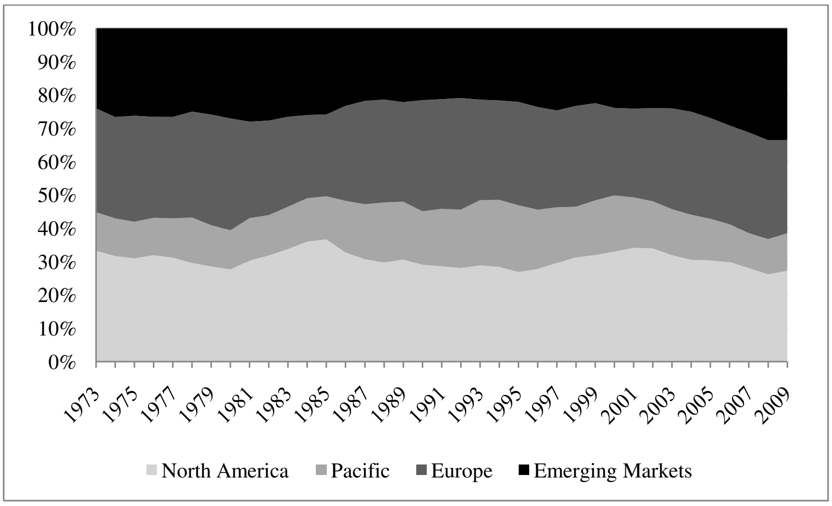


Figure 5.4: Time Series Evolution of Portfolio Weights of a GDP-Weighted Stock Index

This figure depicts the portfolio weights of a GDP-weighted stock index constructed from the MSCI indices for North America, Europe, the Pacific region and the Emerging Markets over the sample period. Data sources are the World Bank for the period 1973-2005 and the International Monetary Fund for the period 2006-2008.



in our analysis. To transfer the idea from the firm to the regional level, we weight the four MSCI indices based on the relative GDP of their covered countries. As the MSCI indices themselves are market-value weighted, this policy might be considered a compromise between a cap-weighted and a fundamentally weighted approach. As can be seen from Figure 5.4, this procedure indeed results in a less volatile, more balanced allocation.

5.3.2.2 Diversification over Asset Classes

The easiest asset allocation policy for private investors would arguably be to assign time-invariant weights to stocks, bonds and commodities. The high number of potential fixed-weight strategies requires the definition of a benchmark against which Markowitz-based models can be tested. As selecting any specific strategy is a somewhat arbitrary choice, we employ a two step procedure. First, we screen the literature to derive a promising baseline policy which we use in the empirical tests in section 5.4.2.2. Second, we analyze the performance of more than 5,000 alternative portfolios with any possible fixed-weights (in 1% steps) in section 5.4.3 to assess the robustness of time-invariant allocation policies.

Regarding the ratio of stocks and bonds, we try to determine a best practice solution as a benchmark. Specifically, we study the security market advice of major investment bankers and brokerage firms as reported in e.g. Annaert et al. (2005) and Arshanapalli et al. (2001) as well as institutional holdings as reported in e.g. Blake et al. (1999), Brinson et al. (1986) and Ibbotson and Kaplan (2000)). Most of these studies analyze the allocation over cash, bonds and stocks and do not consider other asset classes. We focus on the time-series average of the cross-sectional mean of these allocations, as Annaert et al. (2005) and Arshanapalli et al. (2001) document the efficiency of such a strategy. Based on the overall picture, we derive a consensus recommendation of roughly 60% stocks and 40% bonds. Next, we analyze the literature that explicitly deals with commodities in an asset allocation context. Based on e.g. Erb and Harvey (2006) and Anson (1999), we estimate a consensus weight of roughly 15% for commodities.

Constructing an ex-ante baseline portfolio from these results leaves us with some degrees of freedom. Specifically, commodities could be incorporated at the expense of less stocks, less bonds or less stocks and less bonds. Given this arbitrary choice, we use stocks, bonds and commodities in a fixed proportion of 60%, 25% and 15%. Note again that our objective is just to derive a plausible ex-ante strategy as a starting point for the empirical analysis, not an ex-post optimal portfolio.[11]

5.4 Empirical Analysis

5.4.1 Performance Evaluation Methodology

The performance of the portfolio strategies is assessed over the sample period from February 1973 to December 2009. Our implementation of the Markowitz-based models relies on a "rolling-window" approach, i.e. we distinguish between estimation and evaluation period. Specifically, at the beginning of each February, we use return data of the previous 60 months to calculate the input parameters needed to determine the portfolio weights of each index. Using these weights, we then calculate the portfolio returns over the next 12 months without rebalancing. The following February, new portfolio weights are determined by using the updates of the parameter estimates.

We use the resulting time series of out-of-sample returns to compute the Sharpe ratio of each strategy. The ratio is defined as the average monthly excess return over the risk free rate, divided by the standard deviation of monthly excess returns in the whole sample period. To test for differences in Sharpe ratios, we follow the bootstrap technique recently developed in Ledoit and Wolf (2008).

For the market value-weighting scheme, we calculate the portfolio weights at the rebalancing date using market values as of January, 1st. The one month lag has the aim of ensuring real-time data availability. The GDP-weighting is based on GDP-data from the previous year. We also compute the portfolio turnover of each strategy which results from the annual adjustment of the portfolio weights. This allows us to estimate the transaction costs associated with each strategy and to calculate the out-of-sample Sharpe ratio after costs. In order to do so, we assume a proportional bid-ask-spread s equal to 40 basis points per transaction.[12] Then, the costs c_t due to portfolio rebalancing in month t can

[11] In fact, we find that our baseline heuristic performs slightly worse than the other two alternatives. Hence, from an ex-post perspective, the benchmark against which we test scientific asset allocation models might be regarded conservative.

[12] The spread is assumed to be the same for each index. It is based on the average bid-ask spread in 2007 for selected exchange-traded funds tracking the indices used in our analysis. Other trading costs and a potential price impact are

be estimated as follows:

$$c_t = s \cdot \sum_{i=1}^{N} |w_{i,t} - w_{i,t-}|, \tag{5.1}$$

where $w_{i,t}$ is the intended portfolio weight, $w_{i,t-}$ is the portfolio weight before rebalancing and the expression $\sum_{i=1}^{N} |w_{i,t} - w_{i,t-}|$ defines total portfolio turnover.

For international equity diversification, we also rely on factor models commonly employed in the mutual fund literature. Specifically, in addition to the Jensen (1968) one factor alpha, we estimate the alpha from a global Carhart (1997) four factor model to infer to what extent competing strategies load on the value, size and momentum premium. The Carhart (1997) alpha is estimated from the following model:

$$r_t - r_{f,t} = \alpha^{4F} + \beta_{MKT} \cdot MKT_t + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{WML} \cdot WML_t + \epsilon_t, \tag{5.2}$$

where r_t and $r_{f,t}$ are the returns of strategy and the risk-free asset in period t and MKT_t is the excess return of the market-weighted global equity portfolio. The expressions SMB, HML, and WML denote the returns of the following zero-investment strategies: SMB is the return difference between small and large capitalization stocks, HML is the return difference between stocks with high and low book-to-market ratios and WML is the return difference between stocks with high and low past stock returns. The Jensen (1968) one factor alpha is calculated in a similar fashion but uses only the market factor. We construct the global factors using Datastream's world-wide stock universe. Our computation of the factors follows the instructions outlined on Kenneth French's website and employs the methodology of Griffin (2002). That is, the global factors are market weighted averages of the country-specific components. The appendix provides the reader with a detailed description of the construction of the size, value and momentum factors.

For the asset allocation case, we develop a framework aimed at decomposing the portfolio returns of the competing strategies. In the first step, we run a time-series regression of the excess return of each model on the following three factors:

---

neglected. These costs should be marginal for broad-based indices, though.

$$r_t - r_{f,t} = \alpha^{3F} + \beta_1 \cdot Stocks_t + \beta_2 \cdot Bonds_t + \beta_3 \cdot Commodities_t + \epsilon_t, \tag{5.3}$$

where $Stocks_t$, $Bonds_t$ and $Commodities_t$ represent the excess after-cost returns of the stock, bond and commodity market, respectively. The economic interpretation of the coefficients is as follows. The betas represent the linear combination of asset class returns which best approximates the time-series of returns as generated by the model. In this sense, it gives an indication of the fixed-weight strategy that comes closest to the model's performance. For our heuristics, the alpha might be interpreted as the monthly return contribution of the rebalancing approach. For the Markowitz-based models, it might be regarded as the impact of the models' market timing on the overall portfolio return. For instance, minimum variances approaches are expected to, on average, heavily rely on bonds and much less on stocks and commodities. However, in some years, they might exhibit a substantially different asset allocation, as the models attempt to profit from uncommon changes in the risk-return-structure of the input parameters. The alpha from the regression picks up the success from this market timing strategy.

In the second step, we extent this baseline approach to gain additional insights. To this end, we first construct zero-cost, long-short value and momentum portfolios for both bonds and commodities. Our methodology (see the appendix for details) closely follows recent work by Asness et al. (2009), who develop simple, intuitive value and momentum measures for these asset classes. The resulting factors can be thought of as proxies for return premia, which, so far, have primarily been studied exclusively in the stock market. Our approach allows us to analyze to what extent portfolio returns generated by competing asset allocation models are driven by loadings on these common factors. Specifically, we augment the regression specification as given above with three value factors (for stocks, bonds, commodities), three momentum factors (for stocks, bonds, commodities) as well as a size factor (for stocks only).[13]

[13] Data required for the construction of bond value and bond momentum factors is only available for the second subperiod (1988-2009) of our analysis. For the sake of comparability, we thus report results from both our three and ten factor regression only for this period. However, the qualitative nature of our findings from the three factor model does not change if we rely on the full sample period (1973-2009). Note further that, judging from the inspection of correlations and variance inflation factors, multicollinearity does not seem to be an issue of concern in the case of the ten factor model.

5.4.2 Baseline Results

5.4.2.1 International Stock Market Diversification

We start the empirical analysis with a comparison of the performance of the eleven Markowitz-based models and the various heuristic models for an internationally diversified stock portfolio. Results are reported in Table 5.3.

Columns 2 and 3 show that after-costs average returns and standard deviations tend to be quite similar for most models. The minimum variance approach and its various extensions exhibit, as expected, the lowest fluctuation in returns. However, in economic terms, the reduction in risk, as compared to the standard deviation of the three heuristics, seems small. Consequently, full sample after-costs Sharpe ratios tend to be similar for most approaches. The traditional mean-variance model with short-sale restrictions achieves the highest Sharpe ratio (0.124), but this is only marginally higher than the values of the GDP- and naively-weighted portfolio heuristics (0.120 and 0.122, respectively). The value-weighted heuristic performs somewhat worse with a Sharpe ratio of 0.098, suggesting that it might be a less efficient diversification strategy.

To more formally address this issue, we analyze all pairwise differences in Sharpe ratios between the Markowitz models and the three heuristics using the bootstrap technique developed in Ledoit and Wolf (2008). For the sake of brevity we only report p-values for the hypothesis that the Sharpe ratio for each of these models equals the Sharpe ratio of the GDP-weighted stock portfolio in Table 5.3, but using any of the other heuristics as benchmark does not change the qualitative nature of our results. We find that none of the scientific models significantly outperforms any of the three heuristics. Comparing the three heuristics against each other, the outperformance of the GDP-weighted over the popular value-weighted stock portfolio is marginally significant (p-value: 0.08).

To explore potential reasons for the widespread lack of statistical significance, we also examine the performance separately for two subperiods. Results are reported in columns 6 and 7 of Table 5.3. In general, there is no consistency in ranking across subperiods. For instance, the traditional mean-variance model exhibits the highest Sharpe ratio in the second subperiod (1988-2009), but fails to add value over any of the heuristics in the first subperiod. Overall, the analysis suggests that there is no dominating approach.

Table 5.3: Markowitz vs. Heuristics: International Stock Market Diversification Results

This table reports means, standard deviations, Sharpe ratios and alphas of monthly out-of-sample returns after costs as well as average turnover for the international equity portfolios which are constructed using the various Markowitz-based optimization models and heuristic models. Sharpe ratios are reported for the total sample period (1973-2009) and two sub-sample periods (February 1973-January 1988 and February 1988-December 2009). P-values that the Sharpe ratio for each of these models is different from that for the GDP-weighted stock portfolio, our baseline heuristic, are calculated using the bootstrap technique developed in Ledoit and Wolf (2008). We assume a bid-ask spread of 40 basis points to calculate after-cost returns. α^{1F} is the Jensen (1968) one factor alpha; α^{4F} is the Carhart (1997) four factor alpha. For the t-statistics, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. See table 5.2 for a description of the models. Details on the construction of the factors used in the regression framework are given in the appendix.

Portfolio Model	Mean Return	Std. Dev. Return	Mean Annual Turnover	Sharpe Ratio 1973-2009	Sharpe Ratio 1973-1988	Sharpe Ratio 1988-2009	p-value $H_0: SR = SR_{gdp}$	α_{1F}	t-stat α_{1F}	α_{4F}	t-stat α_{4F}
Panel A: Markowitz-based Optimization Models											
maxsr	1.18%	5.87%	57.69%	0.124	0.121	0.126	0.87	0.23%	1.61	0.23%	1.48
minvar-nb	0.92%	4.56%	31.29%	0.102	0.166	0.060	0.51	0.06%	0.64	-0.04%	-0.46
minvar	1.00%	4.62%	23.41%	0.118	0.166	0.087	0.93	0.11%	1.73*	0.03%	0.48
js	1.01%	5.15%	75.44%	0.108	0.121	0.099	0.59	0.11%	0.94	0.11%	0.93
js-ccm	0.99%	5.15%	70.64%	0.105	0.125	0.093	0.53	0.10%	0.84	0.13%	1.05
ccm-maxsr	1.08%	5.64%	58.97%	0.112	0.125	0.106	0.77	0.15%	1.13	0.18%	1.23
ccm-minvar	0.98%	4.62%	19.19%	0.114	0.158	0.084	0.73	0.09%	1.40	0.04%	0.58
nc1v	0.93%	4.57%	31.42%	0.105	0.166	0.065	0.58	0.07%	0.79	-0.03%	-0.29
nc1r	1.00%	4.59%	27.32%	0.119	0.166	0.088	0.96	0.12%	1.66*	0.03%	0.35
nc2v	0.94%	4.58%	28.28%	0.107	0.166	0.068	0.55	0.07%	0.93	-0.02%	-0.33
nc2r	0.98%	4.60%	25.94%	0.115	0.166	0.082	0.81	0.10%	1.50	0.01%	0.17
Panel B: Heuristic Models											
gdp	1.03%	4.84%	11.08%	0.120	0.155	0.098	.	0.12%	2.36**	0.08%	1.54
macap	0.92%	4.79%	4.80%	0.098	0.157	0.060	0.08	0.00%	0.00	0.00%	0.00
naiv	1.04%	4.83%	12.85%	0.122	0.176	0.090	0.77	0.13%	2.42**	0.08%	1.42

Alphas from time-series regressions of portfolio returns on a global one factor Jensen (1968) or four factor Carhart (1997) model do not lead to a different conclusion. Four models (two minimum variance models and the naively- and GDP-weighted heuristic) exhibit a positive, statistically significant and economically meaningful one factor alpha, but this vanishes once one controls for global momentum, value and size effects. This result highlights the importance of well-known risk premia for global index construction and portfolio optimization, which is not seen from an analysis of the Sharpe ratio or Jensen's alpha alone. For instance, we find that the GDP-weighted global stock portfolio loads significantly on the premia associated with the international value and size factor, which prevents its excess return from remaining statistically significant. With regard to the value factor, we find a similar behavior also for the equal-weighted portfolio as well as for all minimum variance approaches. A complete overview of the factor loadings associated with the portfolio models is given in the appendix.

Our analysis is based on after-cost returns because we are interested in whether Markowitz models add value under realistic conditions. It is a natural question to ask whether higher transaction costs prevent the Markowitz models from achieving a better performance, in particular as these models are only optimal under the assumption of no transaction costs. If so, it might still be worthwhile to set up a Markowitz approach to manage an equity portfolio, but to impose certain trading restrictions. As Table 5.3 shows, the mean turnover of all Markowitz-based models is indeed substantially larger than the turnover of the heuristics. However, its economic impact on our results is weak. Even before costs, none of the Markowitz models is able to significantly outperform any of the heuristics. Nevertheless, assuming higher transaction costs (than 40 bp) and more frequent (than yearly) rebalancing generally works in favor of the heuristic models.

5.4.2.2 Diversification over Asset Classes

In the following, we include bonds and commodities in the baseline analysis. Again, we compare the performance of eleven scientific portfolio choice models with three heuristics. The latter only differ in their stock weighting scheme (value-weighted, equal-weighted, GDP-weighted). The proportion invested in bonds (25%) and commodities (15%) is the same across heuristics and motivated by the literature survey in section 5.3.2.2. In section

5.4.3, we extensively vary these portfolio weights to assess the sensitivity of our findings.

Table 5.4 shows the main results. Compared to the international diversification in the stock market, there is less homogeneity in mean returns, standard deviations and Sharpe ratios across models. The minimum variance approach with short-sale constraints and shrunk covariance matrix ($ccm - minvar$) achieves the highest Sharpe ratio (0.161). In contrast, other Markowitz-based strategies exhibit poor risk-adjusted returns. For instance, the Sharpe ratio of the traditional mean-variance model with short-sale restrictions ($maxsr$) is only 0.110, which is even lower than in the case of international equity diversification. Hence, not all Markowitz approaches are able to realize the diversification potential of additional asset classes.

The performance of the fixed-weight heuristics is between the best and worst performing Markowitz models. However, p-values reported in Table 5.4 reveal that we cannot reject the hypothesis of equal Sharpe ratios for the 60-25-15 asset allocation policy with GDP-weighting and any of the optimization models. In unreported results, we find that the same holds true when using the other heuristics as benchmark.

The evidence supports the conclusion that scientific portfolio choice models are not able to outperform a passive benchmark, irrespective of whether we focus on international equity diversification or on diversification over asset classes. However, the heterogeneity in Sharpe ratios among the Markowitz models raises the intriguing possibility that some models are better suited to the asset allocation context than others. To investigate this issue, we implement our three and ten factor regression models. The intuition is to decompose the portfolio weights induced by Markowitz-based approaches in a fixed-weight and a time-varying component. In that sense, Markowitz models are similar to the heuristic portfolio strategies. In contrast to the latter, however, the time-varying component does not reflect the contribution from simple rebalancing back to the original asset allocation, but the attempt to exploit recent changes in the return and risk characteristics of the asset classes in order to optimize the portfolio. Our regression framework picks up both the fixed-weight and the time-varying contribution to portfolio performance. The betas give an indication of which linear combination of fixed-weight asset allocation schemes would give a similar return time-series as the Markowitz models themselves. The alphas might be interpreted as the additional value stemming from the time variation in portfolio

Table 5.4: Markowitz vs. Heuristics: Asset Allocation Results

This table reports means, standard deviations and Sharpe ratios of monthly out-of-sample returns after costs as well as average turnover for the asset allocation portfolios which are constructed using the various Markowitz-based optimization models and heuristic models. Sharpe ratios are reported for the total sample period (1973-2009) and two sub-sample periods (February 1973-January 1988 and February 1988-December 2009). P-values that the Sharpe ratio for each of these models is different from that for the 60-25-15 asset allocation portfolio with GDP-weighting in the stock market, our baseline heuristic, are calculated using the bootstrap technique developed in Ledoit and Wolf (2008). We assume a bid-ask spread of 40 basis points to calculate after-cost returns. α^{3F} is the intercept from a three factor model including the market, bond and commodity factor; α^{10F} is is the intercept from a ten factor model, augmented by value, size and momentum factors. Data required for the construction of bond value and bond momentum factors is only available for the second subperiod (1988-2009) of our analysis. For the sake of comparability, we thus report results from both our three and ten factor regression only for this period. For the t-statistics, * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level. See table 5.2 for a description of the models. Details on the construction of the factors used in the regression framework are given in the appendix.

Portfolio Model	Mean Return	Std. Dev. Return	Mean Annual Turnover	Sharpe Ratio 1973-2009	Sharpe Ratio 1973-1988	Sharpe Ratio 1988-2009	p-value $H_0: SR = SR_{gdp}$	α_{3F}	t-stat α_{3F}	α_{10F}	t-stat α_{10F}
Panel A: Markowitz-based Optimization Models											
maxsr	0.86%	3.74%	49.01%	0.110	0.179	0.052	0.54	-0.09%	-0.64	-0.16%	-1.05
minvar-nb	0.59%	1.13%	13.23%	0.128	0.167	0.097	0.86	-0.02%	-0.75	-0.03%	-1.07
minvar	0.63%	1.11%	7.29%	0.160	0.185	0.139	0.79	0.01%	0.43	-0.01%	-0.32
js	0.75%	2.79%	45.29%	0.109	0.179	0.044	0.55	-0.09%	-0.86	-0.10%	-0.95
js-ccm	0.83%	3.03%	44.91%	0.126	0.186	0.080	0.76	-0.02%	-0.12	-0.02%	-0.15
ccm-maxsr	0.73%	3.70%	53.11%	0.077	0.180	-0.005	0.21	-0.28%	-2.06**	-0.35%	-2.41**
ccm-minvar	0.63%	1.13%	6.11%	0.161	0.182	0.144	0.77	0.00%	0.44	-0.01%	-1.01
nc1v	0.59%	1.13%	13.42%	0.130	0.168	0.099	0.88	-0.02%	-0.67	-0.03%	-1.02
nc1r	0.62%	1.11%	10.07%	0.150	0.163	0.141	0.90	0.01%	0.54	0.00%	-0.26
nc2v	0.61%	1.12%	9.50%	0.142	0.185	0.107	0.98	-0.02%	-0.83	-0.03%	-1.29
nc2r	0.63%	1.11%	7.29%	0.160	0.185	0.139	0.78	0.01%	0.43	-0.01%	-0.32
Panel B: Heuristic Models											
60-25-15; gdp	0.92%	3.29%	12.95%	0.141	0.184	0.115	.	0.12%	2.86***	0.08%	1.79*
60-25-15; macap	0.85%	3.24%	10.25%	0.123	0.185	0.083	0.11	0.02%	1.18	0.00%	-0.23
60-25-15; naiv	0.92%	3.28%	13.61%	0.143	0.205	0.107	0.67	0.10%	2.45**	0.05%	1.18

weights.

However, as shown in the rightmost columns of Table 5.4, there is no additional value. With the exception of one Markowitz model, which has a significant negative three factor alpha, the alphas of all other models are economically close to and statistically not significantly different from zero. Interestingly, the three and ten factor alphas of the fixed-weight heuristics with GDP- and equal-weighting in the stock domain are positive. This result provides further evidence that the value-weighted stock portfolio has not been a particulary successful diversification strategy over the past compared to other potential heuristics.

5.4.3 Variations in the Fixed Weight Asset Allocation Strategy

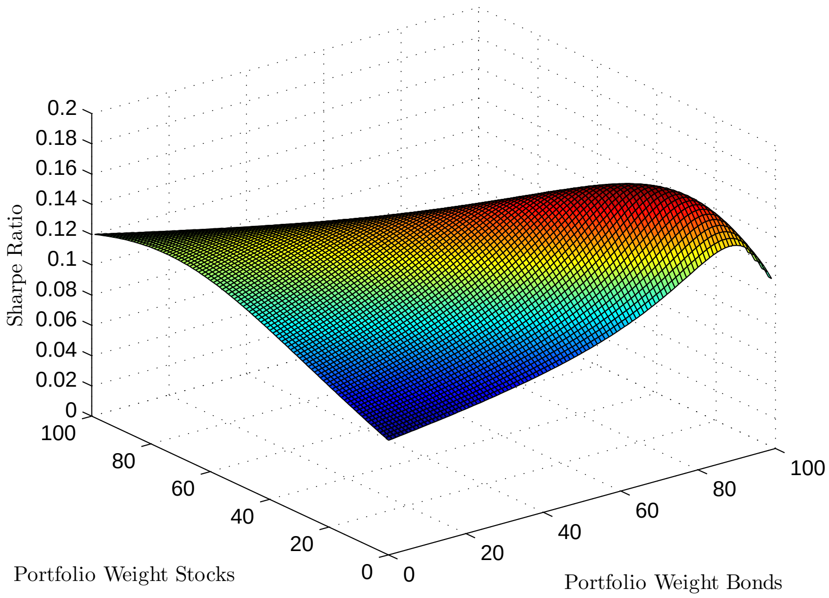
We derive the 60-25-15 asset allocation strategy from the existing literature and use it as a benchmark for the different Markowitz models. One potential concern about this approach may be that the good performance of our baseline heuristic results from backward optimization. To examine whether other possible heuristic strategies perform much worse than our baseline, we calculate the Sharpe ratio after costs for a variety of different fixed-weight asset allocation schemes as well. In constructing the portfolios, we increase the portfolio weight of each asset class in steps of 1% from 0% to 100%, reduce the weight of the second class by the same amount and hold the weight of the third portfolio constituent constant. Imposing a non-negativity constraint for portfolio weights, this approach yields 5,151 different portfolios.[14] The stock component of the portfolios is based on the GDP-weighting approach. Figure 5.5 displays our results. In order to interpret the Figure, note that the portfolio weight of the commodity component indirectly follows from the weights of the two other asset classes. For instance, the portfolio with 0% in stocks and 0% in bonds is completely invested in the commodity index.

Figure 5.5 shows a substantial increase in Sharpe ratios when moving away from portfolios with an extreme portfolio allocation (e.g., 100% of only one asset class). And, furthermore, the slope in the Sharpe ratio becomes flat as we move to the middle of the graph. This

[14]The number of portfolios can be explained as follows. Ignoring short-sale restrictions yields a $N \times N$ matrix of different portfolios, where N equals the number of steps. However, $N \cdot (N-1)/2$ of these portfolios would lead to a short position in one asset class. In our case with 101 steps we have 10,201 portfolios of which 5,050 imply a short position. The difference of 5,151 is the number of portfolios analyzed.

Figure 5.5: Graphical Presentation of the Performance of Alternative Fixed-Weight Asset Allocation Strategies

This figure depicts the Sharpe ratios of alternative heuristic portfolio strategies in the asset allocation context. In constructing the portfolios, we increase the portfolio weight of each asset class at the rebalancing date in steps of 1% from 0% to 100% and adjust the portfolio weights of the other 2 classes appropriately. This approach yields 5,151 different portfolios. The stock component of the portfolios comprises the four regional MSCI indices and is GDP-weighted.



pattern suggests that a wide range of well-balanced allocation approaches over asset classes are able to offer substantial diversification gains. In fact, of the 5,151 tested portfolios, approximately 42% perform better or equal than our baseline heuristic and 58% perform worse. Those that perform worse are very often heavily tilted towards only one asset class. If we subdivide the sample period into the subperiods from 1973-1988 and 1988-2009, the resulting figures look very similar. It follows that the 60-25-15 asset allocation policy is only one out of many different fixed-weight asset allocation schemes which achieve a good performance and which are not dominated by sophisticated academic portfolio models. This is good news for private investors: Although it is not possible to identify the best performing portfolio ex-ante, almost any form of well-balanced allocation of asset classes already offers Sharpe ratios similar to the best performing strategy.

5.4.4 Further Results and Robustness Checks

In this section, we illustrate the economic meaningfulness of our results and verify their robustness in a number of sensitivity checks. These tests differ with respect to the data set, the rebalancing frequency, the input parameter estimation method for the Markowitz models, the implementation of the GDP-weighting heuristic and the performance measure used.

Illustration of Economic Significance: Return Gap

Since differences in Sharpe ratios are hard to interpret from an economic point of view, we also rely on the return gap as a more intuitive performance measure, which is rooted in the risk-matching procedure suggested by Modigliani and Modigliani (1997). By combining the portfolio under consideration with the risk free asset, Modigliani and Modigliani (1997) adjust the volatility of the portfolio to the volatility of the benchmark portfolio. Afterwards, the returns of the combined portfolio can be compared to the returns of the benchmark. More specifically, the return gap, $Return\,Gap_t$, in month t is obtained from the following equation:

$$Return\,Gap_t = r_{bm,t} - [\frac{\sigma_{bm}}{\sigma} r_t + (1 - \frac{\sigma_{bm}}{\sigma}) r_{f,t}], \tag{5.4}$$

where $r_{f,t}$ is the risk-free rate in t, $r_{bm,t}$ stands for the return of the benchmark and σ and σ_{bm} denote the monthly standard deviation of the portfolio and benchmark return over the sample period. We choose the GDP-weighted stock portfolio or the 60-25-15 asset allocation portfolio, our baseline heuristics, as benchmarks. Using the GDP-weighted strategy as a benchmark allows us to assess the benefit of heuristic diversification in the stock universe. Relying on the 60-25-15 strategy as a benchmark is intended to exemplarily quantify the additional benefits obtained from a naive fixed-weight allocation over different asset classes. Table 5.5 verifies that heuristic diversification, both in the stock market and in the asset allocation case, adds value. With the exception of the MSCI Emerging Markets, the GDP-weighted strategy outperforms every stock index as well as bonds and commodities in terms of risk-adjusted return. Including additional asset classes, as implemented in the 60-25-15 portfolio, strengthens these results. The outperformance ranges here from 8.4 to 28.1 basis points per month (or roughly 100 to well more than 300

Table 5.5: Return Gaps of Various Indices Compared to the GDP-Weighted Stock Portfolio and the 60-25-15 Asset Allocation Portfolio

This table reports the Sharpe ratio and Value-at-Risk at the 95% confidence level of monthly returns for various indices as well as the GDP-weighted stock portfolio and the 60-25-15 asset allocation portfolio with GDP-weighting in the stock market, which are our baseline heuristic models for portfolio construction. Moreover, the table presents the Return Gap of these indices in basis points (bp) per month compared to our baseline heuristics. Portfolio weights are readjusted every February each year.

Asset Class/ Region	Sample Period	Sharpe Ratio	VaR 95%	Return Gap (bp per month) GDP-stock portfolio	Return Gap (bp per month) 60-25-15 portfolio
Panel A: Stock Indices					
MSCI Germany	73-09	0.101	-8.95%	7.8	12.4
MSCI France	73-09	0.104	-9.35%	6.2	11.3
MSCI Italy	73-09	0.064	-10.37%	28.1	26.2
MSCI United Kingdom	73-09	0.096	-9.02%	12.5	15.6
MSCI United States	73-09	0.089	-8.30%	15.4	17.6
MSCI Canada	73-09	0.087	-8.65%	16.0	18.0
MSCI Japan	73-09	0.055	-9.04%	30.9	28.1
MSCI Europe	73-09	0.116	-7.75%	1.8	8.4
MSCI North America	73-09	0.093	-8.11%	13.3	16.2
MSCI Pacific	73-09	0.065	-8.61%	26.0	24.8
MSCI Emerging Markets	88-09	0.122	-12.13%	-12.0	-2.2
Panel B: Asset Classes					
GDP-stock portfolio	73-09	0.120	-7.90%	.	7.1
Bonds	73-09	0.108	-1.27%	5.7	11.0
Commodities	73-09	0.076	-9.65%	20.7	21.2

basis points per year) and thus is economically meaningful. Table 5.5 might be interpreted as exemplified evidence that relying on simple rules of thumb in diversifying substantially improves the risk-return profile of the overall portfolio.

Variation in the Data Set

We extensively vary the data set to examine whether our findings are robust with respect to the indices used to represent the asset classes. First, we exclude the MSCI Emerging Markets index which is not available prior to 1988 from the calculations. Second, we rely on the country-specific MSCI indices for the G7 states instead of the regional MSCI indices. Third, we redo our analysis in the asset allocation context using only the MSCI world as the stock market component. Fourth, we also use alternative indices for bonds and commodities.[15] Overall, we find that the variation in the data set does not alter any conclusions drawn in this chapter.

Rebalancing Frequency

Monthly instead of annual rebalancing does not lead to significantly better results before costs for both the scientific portfolio models and the heuristics. After transactions costs, performance tends to deteriorate for most approaches. In general, the performance drop is more severe for the Markowitz models. This is rooted in their higher turnover in combination with their poor market timing abilities, as analyzed in section 5.4.2.2. For the heuristics, the rather minor importance of the rebalancing frequency can also be inferred from the insignficant alphas in Table 5.4 as well as from Figure 5.5. The latter shows that shifts in the portfolio weights are not harmful as long as the portfolio is not too much tilted towards only one asset. In this regard, the major benefit of portfolio rebalancing is to avoid extreme portfolios consisting of mainly only one asset.

Parametrization

In the baseline analysis, we use a time window of 60 months to estimate the input parameters for the Markowitz-based models. To examine whether the performance of these models improves when a longer time-series of historical returns is used for parametrization, we base the estimation method also on a rolling-window approach with 1) 120 months and with 2) all historical data available in a particular month. We do not observe a consistent improvement in the results of the Markowitz models in the additional tests. Furthermore, the out-of-sample Sharpe ratios are still not significantly different from those of the heuristic models.

Implementation of the GDP-weighting Heuristic

We change the methodology of the GDP-weighting scheme in two ways. First, we base portfolio weights on the relative GDP of the next year to proxy for rational expectations. Second, we use GDP weights derived from purchasing power parity (PPP) valuations as provided by the World Bank and the IMF. The performance of the GDP-weighting scheme

[15] Specifically, we replace the iBoxx Euro Overall Index with the iBoxx Euro Sovereign Index, the JPM Global Bond Index and the ML European Monetary Union Index, respectively. Commodities are also represented by the Reuters/Jefferies Total Return Index and the DB Commodity Euro Index, respectively. In most cases this leads to a reduction in the sample size, since most index alternatives have a shorter return data history.

is virtually unchanged in the first check and slightly improves in the second check.

Other Performance Measures

The recent literature has proposed a number of alternative performance ratios. So, we repeat our analysis utilizing asymmetrical performance measures which have been shown to be particularly suited for non-normal return distributions (e.g., Biglova et al. (2004), Farinelli et al. (2008), Farinelli et al. (2009)). Specifically, we employ the Sortino ratio, the Rachev ratio and the Generalized Rachev ratio.[16] The Sortino ratio is computed as the average excess return over the risk free rate divided by the downside volatility of the excess return. The Rachev ratio relies on the conditional value at risk of the excess return. Portfolios with the highest Rachev ratios are the ones which best manage to simultaneously deliver high returns and get insurance for high losses. The General Rachev ratio additionaly takes investors degree of risk aversion into account. Utilizing these alternative measures does not change the qualitative nature of our results. A broad spectrum of heuristic portfolio allocation mechanisms still yields similar results as scientific portfolio choice models. Furthermore, there is no consistency in ranking across performance ratios, which again indicates that there is no overall dominating approach.

5.5 Conclusion

In this study, we examine the investment value of heuristic diversification strategies as a possible remedy against widespread costly investment mistakes. The field of household finance suggests that many private investors do not fully exploit the benefits of diversification and incur non trivial welfare costs as a consequence. Given this context, we ask whether and which simplistic guidelines offer a promising way for investors to diversify. To this end, we compare eleven Markowitz-based optimization methods favored or recently proposed in the literature with a broad range of heuristic allocation strategies, both for international stock market diversification and in the asset allocation case.

Our main results can be summarized as follows. First, for global equity diversification, prominent Markowitz extensions do not outperform heuristic stock weighting schemes.

[16]For a detailed description of these ratios, we refer the reader to Biglova et al. (2004) and Rachev et al. (2007). To implement the ratios, we apply the parametrization described in Biglova et al. (2004) and Farinelli et al. (2008).

Global value, momentum and size premiums are important drivers of the portfolio performance of many strategies, both scientific and heuristic. Second, the inclusion of additional asset classes towards a "world market portfolio" is, in general, highly beneficial. Diversification gains are mainly driven by a well-balanced allocation over different asset classes. As long as the portfolio is not heavily tilted towards one asset class, almost any form of naive fixed-weight allocation strategy realizes diversification potential. Third, Markowitz-based optimization methods again do not add substantial value.

Our findings is good news for private investors: Relying on simple rules of thumb in asset allocation significantly improves upon the performance of any single asset class portfolio. Moreover, following these easily implementable strategies does not lead to lower risk-adjusted returns as compared to even very sophisticated and recently proposed portfolio choice models.

Our study suggests several directions for further research. First, provided the availability of reliable data, the analysis could be extended to other asset classes. Eun et al. (2008) and Petrella (2005), for example, argue that investors can gain additional diversification benefits from small and mid caps. Second, alternatives to the estimation of input parameters from historical data could be analyzed. Third, future research should explore whether combining portfolio optimization concepts with heuristic allocation schemes is a fruitful direction. Within a bottom-up approach, for example, minimum variance models could be implemented on an individual asset level (see e.g., Jagannathan and Ma (2003)), while plausible heuristics might be used on an index or asset class level.

Chapter 6

Supplemental Material

6.1 Appendix to Chapter 2

This appendix contains tables and figures that supplement the analysis in chapter 2. Figure 6.1 compares the cumulative distribution functions of shock variables on Epiphany. Table 6.1 gives an overview of the data sets used. Table 6.2 illustrates the distribution of legally recognized holidays across German states. Table 6.3 provides descriptive statistics of the stock market data. Table 6.4 displays the distribution of industry groups across samples. Table 6.5 illustrates the construction of the factors for size, value and momentum. Table 6.6 provides further evidence on the level of differences in shocks in absolute abnormal returns between holiday and non-holiday firms.

Figure 6.1: Comparison of Cumulative Distribution Functions of Shock Variables on Epiphany

The following graph is intended to illustrate the economic magnitude of the difference in shock variables between holiday and non-holiday firms (see section 2.4.3). As the largest difference is observed for Epiphany (see panel A of table 2.4), we employ the following procedure. For each year in which Epiphany falls on a trading day, we compute the empirical cumulative probably distribution of the shock variable for holiday firms and separately for non-holiday firms. To obtain an overall distribution, we then average the resulting percentiles across time. This approach resembles the procedure used in the analysis relied on in the paper, which aimed at obtaining an estimate for the shock variable of the median firm. The following graph shows the two cumulative distribution functions. For better readability, only values above the 5th percentile and below the 95th percentile are displayed.

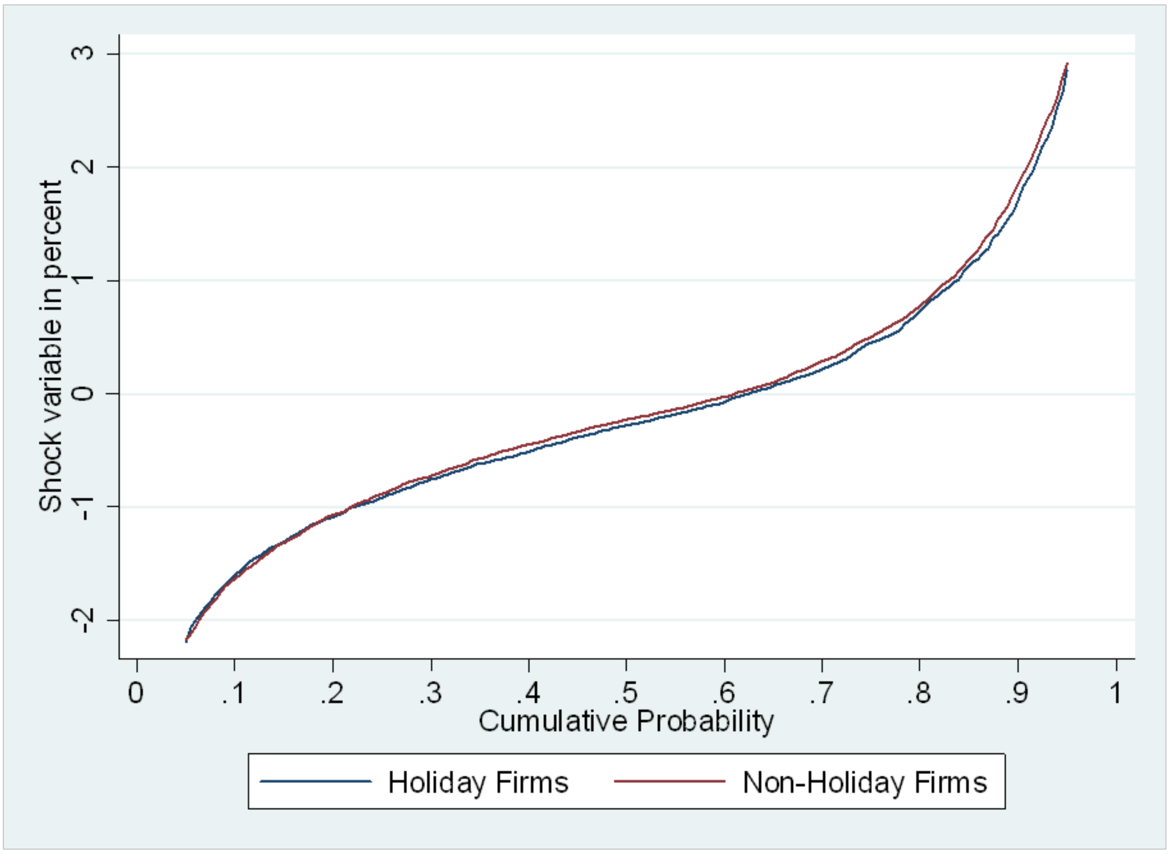


Table 6.1: Overview of Data Sets Used in Chapter 2

Data	Data Source	Description	Sample Period
Daily stock market data	Thomson Reuters Datastream	Adjusted and unadjusted daily closing prices, market capitalization, book values, the number of daily shares traded, the number of total shares outstanding, adjustment factors, the primary exchange as well as industry membership for a final sample of 792 stocks of firms headquartered in Germany	June 13, 1988 - January 15, 2009
Daily trading records of retail clients	German Online Discount Broker	316,134 stock transactions of about 3,000 individual investors; out of these, 136,125 transactions are conducted by 2,901 investors with regard to 965 firms headquartered in Germany	January 1, 1997 - April 17, 2001
Analyst coverage	I/B/E/S	Recommendation and review dates for a total of 51,497 stock buy/hold/sell-recommendations published by 196 brokers, covering about 80% of sample firms	January 1, 1993 - December 31, 2008
Media coverage	Genios, Factiva	126,125 hand collected firm-specific news articles published in three leading German daily business papers (Financial Times Deutschland, Sueddeutsche Zeitung, Handelsblatt), covering about 94% of sample firms	January 1, 2000 - January 15, 2009
Ad hoc disclosures and corporate news	Deutsche Gesellschaft fuer Ad-hoc-Publizitaet (DGAP)	Time-stamped ad hoc disclosures for all sample firms, time-stamped corporate news for half of sample firms	January 1, 2000 - January 15, 2009
Internet search frequencies for firm names	Google	Standardized daily time-series of search frequencies for the names of sample firms, constructed from Google's application "Insights for Search"	January 1, 2004 - January 15, 2009
Index membership	Deutsche Boerse AG	Time Series of historical DAX and MDAX index composition	June 13, 1988 - January 15, 2009
Individual investor characteristics	SAVE study	Quantitative information on various economic and socio-psychological characteristics of a broadly representative sample of German individual investors based on a rich panel questionnaire study	Yearly data from 2005 - 2009
Metropolitan regions	Initiative European Metropolitan Regions in Germany	Detailed information on the borders of the eleven German metropolitan areas as defined by the Conference of Ministers for Spatial Planning	
Firm headquarters	Thomson Reuters Datastream, Deutsche Boerse AG, firm homepages	Address of firm headquarter location	

Table 6.2: Legally Recognized Holidays in German States

This tables illustrates the distribution of legally authorized holidays across German states. The illustration is constructed on the basis of an overview provided by the Ministry of the Interior (see www.bmi.bund.de for details). Holidays covered in the analysis (Epiphany, All Saints' Day, Corpus Christi) are highlighted in bold type. Note that, while Reformation Day is another regional holiday (celebrated in most of the former German Democratic Republic), less than 5% of sample firms are located in the affected area (see also figure 1).

Holiday	Date	BW	BA	BE	BRA	BR	HA	HE	MWP	LS	NRW	RP	SAA	SAX	SAXA	SH	TH
New Year's Day	January 1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Epiphany	**January 6**	**X**	**X**												**X**		
Good Friday	Easter Sunday minus 2 days	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Easter Sunday					X												
Easter Monday	Easter Sunday plus 1 day	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
May Day	May 1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Ascension Day	Easter Sunday plus 39 days	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Whit Sunday	Easter Sunday plus 49 days																
Whit Monday	Easter Sunday plus 50 days	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Corpus Christi	**Easter Sunday plus 60 days**	**X**	**X**					**X**			**X**	**X**	**X**				
Augsburger Friedensfest	August 8		A														
Assumption	August 15		k										X				
Day of German Unity	October 3	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Reformation Day	October 31				X				X					X	X		X
All Saints' Day	**November 1**	**X**	**X**								**X**	**X**	**X**				
Day of Repentance	Wednesday before November 31													X			
Christmas	December 25 and December 26	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

X=legal holiday
A=only in Augsburg
k=legal holiday in predominantly catholic municipalities

BW=Baden-Württemberg
BA=Bavaria
BE=Berlin
BRA=Brandenburg
BRE=Bremen
HA=Hamburg
HE=Hesse
MWP=Mecklenburg-Western Pomerania

LS=Lower Saxony
NRW=North Rhine-Westphalia
RP=Rhineland Palatinate
SAA=Saarland
SAX=Saxony
SAXA=Saxony-Anhalt
SH=Schleswig-Holstein
TH=Thuringia

Table 6.3: Summary Statistics Based on Weekly Data

This table provides various summary statistics for our sample based on 792 German firms in the period from June 13, 1988 to January 15, 2009. Panel A describes cross-sectional differences in time-series averages of firm characteristics. *Firm market capitalization* is measured in million Euro. $Firm\ book/market - ratio$ is the balance sheet value of the common equity in the company (Worldscope item 03501) divided by the market value of equity. *Firm turnover* is the weekly number of shares traded scaled by the number of total shares outstanding. *Firm weeks* is the number of weeks the firm is in our sample. Panel B describes time-series characteristics of weekly cross-sectional (equally- and value-weighted) averages. $Number\ of\ firms$ is the number of active firms in our sample in a given week.

Panel A: Cross-sectional Statistics					
Variable	Mean	Median	SD	5th Percentile	95th Percentile
Firm return	0.09%	0.16%	0.58%	-0.95%	0.67%
Firm return volatility	7.33%	6.37%	5.99%	2.97%	12.94%
Firm market capitalization	1,148	123	4,704	17	4,190
Firm book/market-ratio	0.52	0.44	1.36	0.09	1.04
Firm turnover	1.42%	0.93%	1.68%	0.01%	4.55%
Firm weeks	556	515	322	95	1,075
Panel B: Time-series Statistics					
Variable	Mean	Median	SD	5th Percentile	95th Percentile
Value-weighted return index	0.16%	0.31%	2.54%	-4.22%	3.96%
Equally-weighted return index	0.21%	0.35%	1.73%	-2.69%	2.48%
Value-weighted turnover index	2.04%	1.86%	0.98%	0.80%	3.69%
Equally-weighted turnover index	0.98%	0.85%	0.56%	0.33%	2.09%
Number of firms	411	409	151	183	620

Table 6.4: Distribution of Industry Groups Across Holiday and Non-Holiday Regions

This table shows the concentration and composition of industries (as given by the Datastream Level 2 industry classification) across holiday and non-holiday regions for the case of Epiphany, All Saints' Day, and Corpus Christi, respectively. Panel A (B) shows an equal-weighted (value-weighted) analysis, where the weight of each industry group is determined by the fraction of holiday firms in that industry group (by the relative market capitalization of industry group observations). In Panel B, DAX 30 blue chips (about 6% of observations) are excluded to prevent a small fraction of large firm dominating the analysis. In both panels, the Herfindahl index of industry concentration is computed as the sum of squared industry group weights.

Industry	Epiphany		All Saints' Day		Corpus Christi	
	Holiday	Non-Holiday	Holiday	Non-Holiday	Holiday	Non-Holiday
Total number of firms	301	491	509	283	603	189
	Panel A: Equal-Weighted Analysis					
Herfindahl index of idustry concentration	0.15	0.15	0.15	0.16	0.15	0.15
Oil, Gas, Alternative Energy	3.32%	3.67%	2.75%	4.95%	2.65%	6.35%
Basic Materials	5.98%	7.13%	7.27%	5.65%	6.80%	6.35%
Industrials	22.26%	21.59%	22.79%	20.14%	22.39%	20.11%
Consumer Goods	17.28%	14.66%	16.11%	14.84%	15.92%	14.81%
Health Care	5.65%	6.11%	4.52%	8.48%	5.31%	7.94%
Consumer Services	7.97%	8.15%	9.23%	6.01%	7.96%	8.47%
Telecommunications	0.33%	1.02%	0.98%	0.35%	0.83%	0.53%
Utilities	4.32%	2.44%	4.13%	1.41%	3.65%	1.59%
Financials	18.27%	22.20%	18.27%	25.09%	19.90%	23.28%
Technology	14.62%	13.03%	13.95%	13.07%	14.59%	10.58%
	Panel B: Value-Weighted Analysis					
Herfindahl index of idustry concentration	0.16	0.16	0.17	0.18	0.17	0.17
Oil, Gas, Alternative Energy	3.37%	3.79%	1.73%	4.79%	1.61%	14.41%
Basic Materials	8.56%	9.81%	10.06%	8.13%	10.59%	7.90%
Industrials	20.44%	20.99%	23.25%	19.22%	21.16%	16.32%
Consumer Goods	14.11%	12.59%	12.31%	10.40%	12.64%	8.24%
Health Care	3.52%	7.81%	3.06%	12.34%	4.37%	2.22%
Consumer Services	6.39%	7.22%	7.82%	4.63%	6.92%	7.63%
Telecommunications	1.25%	0.57%	0.93%	0.77%	0.65%	1.47%
Utilities	12.18%	3.53%	8.59%	1.57%	7.74%	3.54%
Financials	25.57%	26.59%	26.54%	31.07%	28.97%	30.97%
Technology	4.61%	7.10%	5.70%	7.08%	5.34%	7.30%

Table 6.5: Construction and Summary Statistics of Factors for Size, Value, and Momentum Relied on in Chapter 2

The factors for size, value and momentum are constructed from the daily stock returns of those firms which survive the screening process as outlined in section 2.3. The screening process is designed to exclude very small and illiquid stocks and to identify firms with available and reliable stock market data. This procedure results in a final sample of 792 firms headquartered in Germany. With regard to the construction of value and size portfolios, we follow very closely the methodology proposed in Fama and French (1993). Specifically, in each year at the end of June, we form six value-weighted portfolios based on firm size and equity book-to-market ratio. A firm's equity book-to-market ratio is defined as the balance sheet value of the common equity in the company (Worldscope item 03501) divided by the market value of equity. To qualify for the inclusion in any of the portfolios, a firm has to meet the following requirements: 1) The stock must have valid price data at the end of June (i.e. no previous delisting and not being discarded by the screening process. 2) The book as well as the market value as computed at the end of December of the previous year have to be non-negative. To sort stocks into portfolios, we form three book-to-market equity groups (low, medium, high) based on the 30th and 70th percentile of the book-to-market-ratio as well as (independently) two size equity groups (small, big) based on the median of the market capitalization. From the intersections of these groups, the following six portfolios are constructed: Small Low, Small Medium, Small High, Big Low, Big Medium, Big High. Daily value-weighted returns on the six portfolios are calculated from the beginning of July to the end of June of the next year. The portfolios are reformed yearly. Daily factor returns for size (SMB) and value (HML) are then calculated as follows: $SMB = 1/3(SmallLow + SmallMedium + SmallHigh) - 1/3(BigLow + BigMedium + BigHigh)$ and $HML = 1/2(SmallHigh + BigHigh) - 1/2(SmallLow + BigLow)$. With regard to the momentum factor, we follow very closely the methodology proposed in Carhart (1997). Specifically, we form three equally-weighted portfolios, split by the 30th and 70th percentile of the distribution of the most recent eleven-months return lagged one month (i.e. the most recent month is skipped). This results in three momentum-sorted portfolios (Winners, Neutral, Losers), which are reformed monthly. To be included in any of the portfolios, the stock must have valid price data for the whole previous year (i.e. no previous delisting and not being discarded by the screening process). Daily returns for the momentum factor (WML) are then calculated as follows: $WML = Winners - Losers$. The following table shows summary statistics of factor returns based on monthly data from June 1988 to January 2009 (236 observations). Monthly frequency is chosen to facilitate comparison with other studies. The table displays monthly return summary statistics for the market factor (RMRF), the size factor (SMB), the value factor (HML) and the momentum factor (UMD). The market factor is computed as the monthly return of the CDAX minus the monthly risk-free rate. The CDAX is a broad German stock index with several hundred constituents. According to the index provider Deutsche Boerse Group, it reflects the performance of the overall German equity market.

Factor	Mean	Std. Dev.	t-statistic: mean=0	Min	Max
RMRF	0.25%	5.79%	0.67	-19.90%	18.63%
SMB	-0.24%	3.50%	-1.05	-13.12%	12.77%
HML	1.01%	2.86%	5.44	-8.76%	9.90%
WML	0.68%	4.65%	2.26	-22.77%	14.09%

Table 6.6: Difference in Shocks in Absolute Abnormal Returns: Further Evidence

This table provides supplementary material for the test on differences in shocks in absolute abnormal returns, as described in section 2.4.3. Panel A reports differences in mean shocks in absolute abnormal returns. To this end, daily absolute abnormal returns for each firm during t-5 to t+5, as obtained from a German version of the Carhart (1997) four factor model, are computed. Factor loadings are estimated from time-series regressions from t-66 to t-6. For both the holiday and the non-holiday sample, firm-specific shocks are computed as the absolute abnormal return at t minus the average absolute abnormal return in t-5 to t+5 (excluding t). The table reports the difference between the mean shock value for the holiday sample and the mean shock value for the non-holiday sample, averaged across years. To mitigate the effect of extreme outliers, we winsorize the data at the 1% and 99% level before computing the mean. This is done for the holiday and non-holiday sample in each year separately. Statistical significance is assessed by bootstrapping as described in footnote 11. *Large firms* (*Small firms*) refer to stocks with a market value larger (smaller) than the median stock, measured at the beginning of the year. Statistical significance at the ten, five and one percent level is indicated by *, **, and ***, respectively. Panel B compares the frequency of extreme return events on the event day. To this end, all holiday (non-holiday) firm-level shocks are pooled. *Shock variable at least* 0% means that the idiosyncratic component of the stock's return on the event day has at least the same importance as on average in a nearby benchmark period (t-5 to t+5, excluding t). The odds ratio is computed as the ratio of the fraction of extreme events for holiday firms and the fraction of extreme events for non-holiday firms.

Panel A: Difference in Mean Shocks in Absolute Abnormal Returns

Dependent Variable	Epiphany	All Saint's Day	Corpus Christi	Pooled
Abnormal absolute return: All firms	-0.08%*	0.02%	-0.07%	-0.04%
Abnormal absolute return: Large firms	-0.09%**	0.00%	-0.08%	-0.06%*
Abnormal absolute return: Small firms	-0.07%	0.02%	-0.06%	-0.03%

Panel B: Frequency of Extreme Return Events on the Event Day

Event	Holiday Firm Observations	Non-Holiday Firm Observations	Odds Ratio
% of Observations with Shock Variable at least 0%	34.57%	37.09%	0.93
% of Observations with Shock Variable at least 1%	15.22%	16.04%	0.95
% of Observations with Shock Variable at least 2%	7.63%	8.68%	0.88

6.2 Appendix to Chapter 3

This appendix contains figures and tables that supplement the analysis in chapter 3. Figures 6.2 to 6.4 illustrate the relationship between specific characteristics of abnormal industry-level returns and resulting distraction proxy decile ranks. Figure 6.5 shows the empirical cumulative distribution function of the return on US stock pairs sorted by distraction proxy decile ranks as observed on the day of divergence. Table 6.7 gives an overview of the data samples used in the study. Table 6.8 reports distribution details of the return on US stock pairs sorted by distraction proxy decile ranks as observed on the day of divergence. Table 6.9 provides descriptive statistics for pairs trading samples in international stock markets. Table 6.10 displays a transition matrix of baseline distraction proxy decile ranks and modified ranks available in real time. Table 6.11 shows findings from multivariate regression when relying on this real-time distraction proxy. Table 6.12 explores the impact of time-varying arbitrage risk on pairs trading profitability. Table 6.13 reports cross-sectional tests (no waiting return computation scheme) on the link between investor distraction and pairs trading profitability.

Figure 6.2: Mean of Abnormal Industry Returns by Distraction Proxy Decile Ranks

The following figures are intended to illustrate the relationship between specific characteristics of abnormal industry-level returns and resulting distraction proxy decile ranks. To this end, we compute, at each day, the mean of different types of abnormal industry returns, where industries are represented by the 49 Fama/French (1997) segments. The upper graph uses (raw) abnormal returns, the middle graph uses absolute abnormal returns, and the lower graph uses weighted absolute abnormal returns, where industry weights are determined by the inverse of the volatility of their shock variables over the previous year. See section 3.2 for a detailed description of how abnormal returns and weights are computed. By distraction proxy decile ranks, the boxes illustrate the 25th, 50th, and 75th percentile of the time-series of the mean of these abnormal returns. The adjacent values in the box plot are the most extreme values within 1.5*interquartile range (75th percentile-25th percentile) of the nearer quartile.

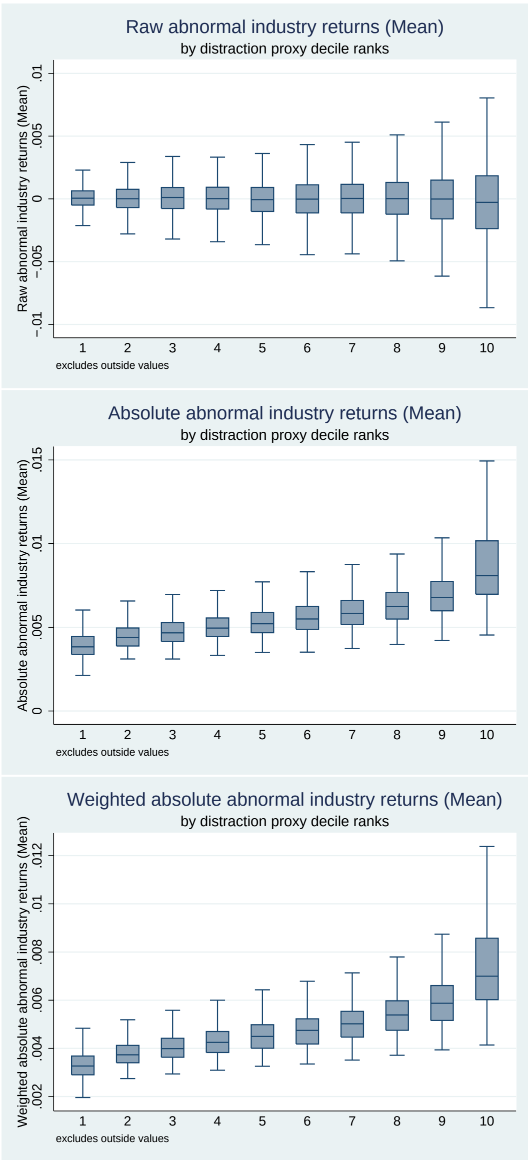


Figure 6.3: Standard Deviation of Abnormal Industry Returns by Distraction Proxy Decile Ranks

The following figures are intended to illustrate the relationship between specific characteristics of abnormal industry-level returns and resulting distraction proxy decile ranks. To this end, we compute, at each day, the standard deviation of different types of abnormal industry returns, where industries are represented by the 49 Fama/French (1997) segments. The upper graph uses (raw) abnormal returns, the middle graph uses absolute abnormal returns, and the lower graph uses weighted absolute abnormal returns, where industry weights are determined by the inverse of the volatility of their shock variables over the previous year. See section 3.2 for a detailed description of how abnormal returns and weights are computed. By distraction proxy decile ranks, the boxes illustrate the 25th, 50th, and 75th percentile of the time-series of the standard deviation of these abnormal returns. The adjacent values in the box plot are the most extreme values within 1.5*interquartile range (75th percentile-25th percentile) of the nearer quartile.

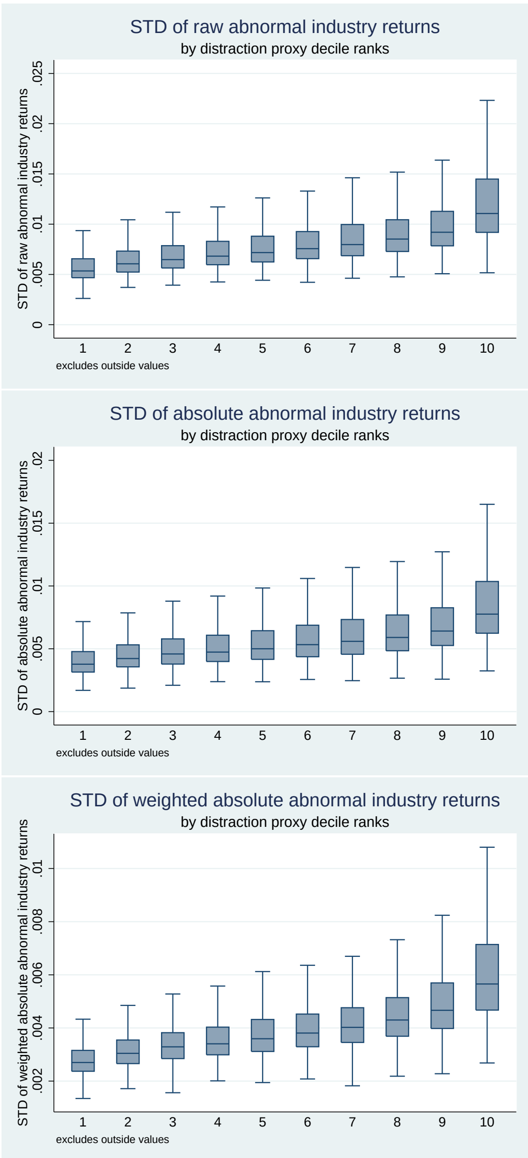


Figure 6.4: Maximum Fraction of a Single Industry Return Shock by Distraction Proxy Decile Ranks

The following figure is intended to illustrate the relationship between specific characteristics of abnormal industry-level returns and resulting distraction proxy decile ranks. To this end, we first compute the baseline distraction proxy as outlined in section 3.2. In short, the proxy is constructed as the sum of weighted absolute abnormal industry returns, where industries are represented by the 49 Fama/French (1997) segments. For each day, we then identify the maximum fraction a single industry return shock accounts for. By distraction proxy decile ranks, the boxes illustrate the 25th, 50th, and 75th percentile of the time-series of this maximum weight. The adjacent values in the box plot are the most extreme values within 1.5*interquartile range (75th percentile-25th percentile) of the nearer quartile.

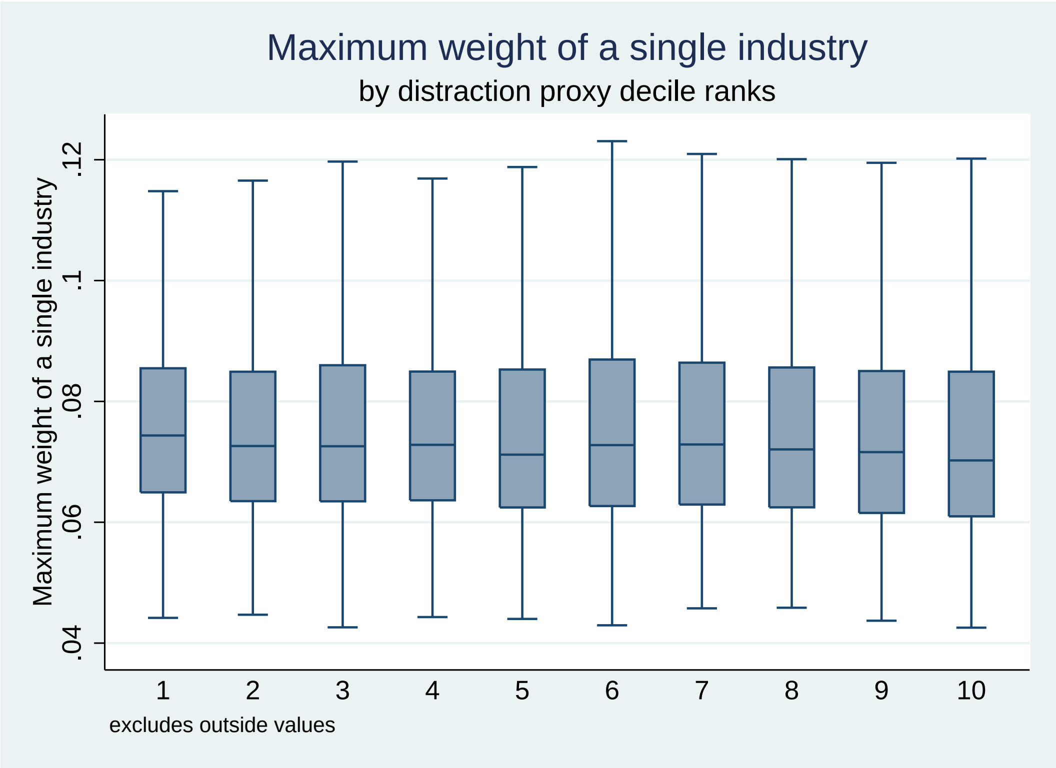


Figure 6.5: Cumulative Distribution Function of Pairs Trading Profits by Distraction Deciles

This figure shows the empirical cumulative distribution function of event-time one-month returns on zero-cost portfolios of US stock pairs sorted by distraction proxy decile ranks as observed on the day of divergence. Breakpoints for the deciles are determined separately for each year. We only consider low distraction days (=decile 1) and high distraction days (=decile 10). In Panel A (B), trading positions in each pair are initiated on the day of divergence (on the day following the convergence) and liquidated on the day of convergence (on the day following the convergence). For better readability, extreme returns (larger than 20% or smaller than -20%) are not shown. Extreme returns account for roughly 1% of all sample observations.

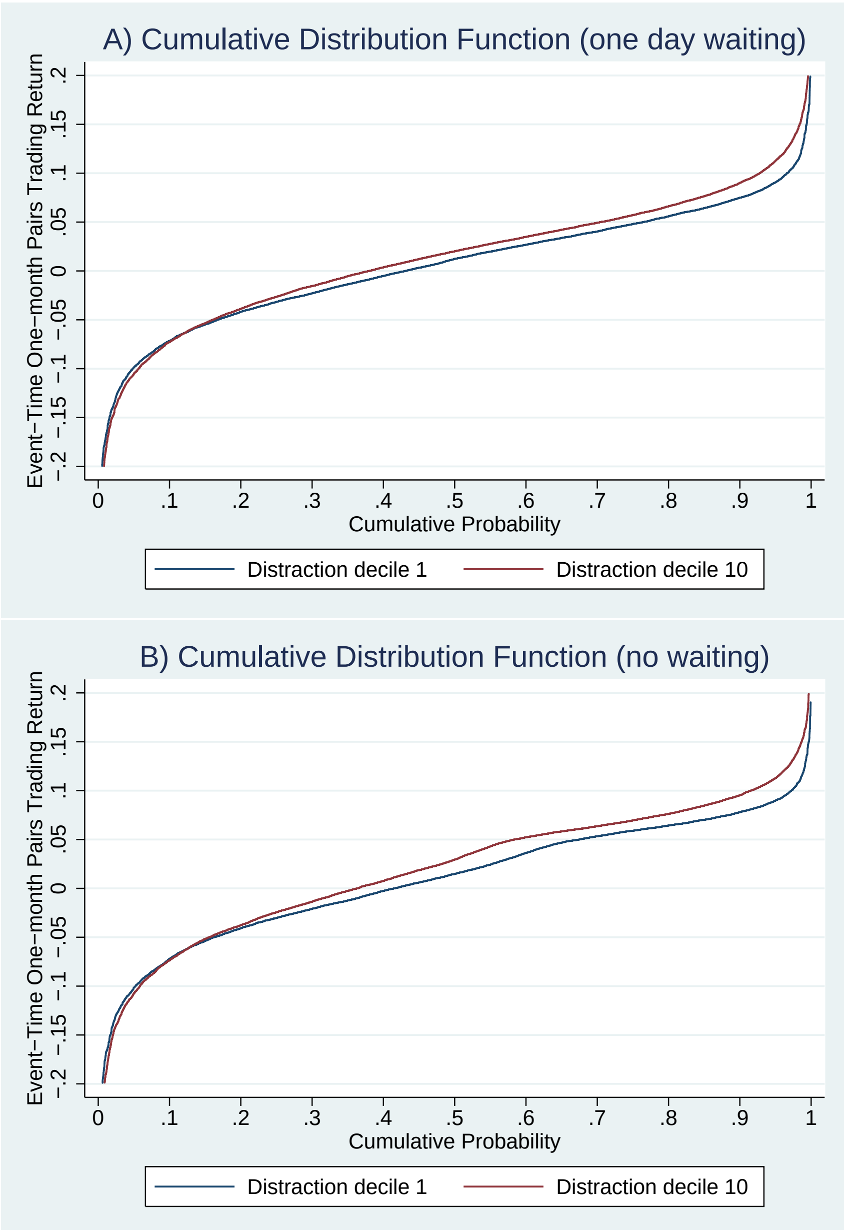


Table 6.7: Overview of Data Sets Used in Chapter 3

Data Source	Description	Sample Period
CRSP	Daily stock market data for all US firms trading on NYSE, AMEX or NASDAQ	January 1960 - December 2008
Compustat Global Daily Stock File	Daily stock market data for firms of eight large non-North American stock markets (Japan, UK, France, Germany, Switzerland, Italy, Netherlands, Hongkong)	Middle of the 1990ies - December 2009
Compustat Fundamentals Annual and Segment Files	Financial information about firm segments based on yearly data	1977-2008
Factiva	Yearly number of Dow Jones News Services articles about each firm that meets data requirements on pairs trading in some period after 1990	1991-2008
I/B/E/S	Number of I/B/E/S analysts for sample firms	January 1980 - December 2008
Kenneth R. French's Data Library	Several portfolio returns and risk factors	Middle of the 1960ies - December 2008
Lubos Pástor's homepage	Traded liquidity factor	January 1968 - December 2008
NBER	US business cycle expansions and contractions based on monthly data	January 1960 - December 2008

Table 6.8: Distribution of One-month Pairs Trading Abnormal Returns by Distraction Deciles

This table reports distribution details of event-time one-month returns on zero-cost portfolios of US stock pairs sorted by distraction proxy decile ranks as observed on the day of divergence. Breakpoints for the deciles are determined separately for each year. Calculations are based on daily data from January 1962 to December 2008. In Panel A (B), trading positions in each pair are initiated on the day of divergence (on the day following the convergence) and liquidated on the day of convergence (on the day following the convergence).

Distraction Decile	All	1	2	3	4	5	6	7	8	9	10
Panel A: One Day Waiting, Full Sample Period (1962-2008)											
N	103,386	8,187	8,679	9,146	9,398	10,048	10,079	10,595	11,019	12,224	14,011
mean	0.97%	0.53%	0.86%	0.77%	0.87%	0.95%	0.94%	1.02%	1.10%	1.09%	1.30%
sd	6.57%	6.20%	6.30%	6.53%	6.32%	6.58%	6.56%	6.54%	6.52%	6.73%	7.05%
p1	-17.83%	-17.23%	-17.08%	-18.08%	-17.37%	-17.04%	-18.70%	-17.72%	-17.73%	-18.06%	-18.59%
p10	-7.04%	-7.16%	-6.60%	-7.02%	-6.95%	-7.02%	-6.95%	-6.98%	-6.94%	-7.28%	-7.28%
p25	-2.73%	-3.16%	-2.73%	-2.77%	-2.70%	-2.76%	-2.61%	-2.70%	-2.58%	-2.68%	-2.64%
p50	1.59%	1.24%	1.41%	1.36%	1.52%	1.57%	1.49%	1.62%	1.71%	1.72%	2.01%
p75	5.23%	4.80%	4.97%	5.05%	5.02%	5.17%	5.24%	5.27%	5.33%	5.47%	5.71%
p90	8.21%	7.49%	7.79%	7.85%	7.90%	.0809082	8.16%	8.28%	8.31%	8.54%	9.00%
p99	15.19%	13.49%	14.62%	14.41%	13.81%	15.04%	15.25%	15.46%	14.92%	16.07%	16.77%
Panel B: No Waiting, Full Sample Period (1962-2008)											
N	104,125	8,222	8,738	9,179	9,436	10,094	10,122	10,657	11,146	12,332	14,199
mean	1.38%	0.89%	1.20%	1.08%	1.23%	1.31%	1.35%	1.33%	1.53%	1.56%	1.90%
sd	6.77%	6.40%	6.41%	6.70%	6.57%	6.75%	6.71%	6.76%	6.69%	6.95%	7.30%
p1	-18.55%	-17.21%	-17.65%	-18.74%	-18.33%	-17.98%	-19.22%	-19.17%	-17.93%	-18.61%	-19.29%
p10	-7.11%	-7.20%	-6.65%	-7.13%	-7.06%	-7.05%	-7.00%	-7.10%	-7.13%	-7.31%	-7.36%
p25	-2.62%	-3.03%	-2.58%	-2.74%	-2.61%	-2.63%	-2.44%	-2.75%	-2.49%	-2.63%	-2.45%
p50	2.14%	1.48%	1.80%	1.68%	1.96%	2.03%	2.09%	2.16%	2.35%	2.54%	2.94%
p75	6.33%	5.90%	5.96%	6.03%	6.11%	6.27%	6.29%	6.33%	6.45%	6.62%	6.95%
p90	8.47%	7.79%	7.99%	8.04%	8.18%	8.33%	8.32%	8.45%	8.57%	8.82%	9.54%
p99	13.80%	12.12%	12.40%	13.12%	12.83%	13.12%	12.99%	13.50%	13.63%	14.30%	15.85%

Table 6.9: Descriptive Statistics for Pairs Trading Samples in International Stock Markets

In panel A, *Total market capitalization* refers to the value reported by Thomson Financial Datastream for the total domestic market capitalization at the year-end 2002, which roughly marks the middle of the sample period for most countries . In panel B, *Number of industries* states how many of the 10 Global Industry Classification Standard (GICS) industry sectors are represented in the pairs trading sample. *Maximum industry weight* denotes the largest fraction of sample firms belonging to a specific industry group. *Industry concentration* is computed as the sum of squared industry weights. In panel C, values are computed analogously for within-pair industry group combinations.

		Japan	UK	France	Germany	Switzerland	Italy	Netherlands	Hongkong
Panel A: Overall Market Characteristics									
Sample period		1/1995-12/2009	1/1995-12/2009	1/1996-12/2009	1/1996-12/2009	6/1997-12/2009	6/1995-12/2009	1/1995-12/2009	1/1995-12/2009
Total market cap. (in billion USD)		2100.19	1819.29	877.87	651.57	540.76	448.22	429.80	417.61
Number of sample firms		4,873	4,867	1,424	1,302	387	500	354	521
Number of firm days (in million)		12.00	6.35	2.11	2.54	0.32	0.47	0.68	0.87
Panel B: Firm Characteristics									
Number of industries		10	10	10	10	10	10	9	10
Max. industry weight	Fraction	26.50%	20.88%	25.88%	21.29%	30.13%	31.65%	26.99%	38.11%
	Industry	Industrials	Cons. Discretionary	Financials	Industrials	Financials	Financials	Financials	Financials
Industry concentration		16.16%	14.81%	16.46%	21.29%	18.07%	18.79%	17.46%	22.16%
Panel C: Pair Characteristics									
Total no. of pairs traded		36,992	27,185	25,833	26,006	16,841	25,596	21,320	20,894
Average turnover	Mean	0.16%	0.44%	0.21%	0.35%	0.43%	0.41%	0.50%	0.56%
at day of divergence	Median	0.09%	0.28%	0.12%	0.20%	0.25%	0.26%	0.28%	0.29%
Cumul. return difference	Mean	6.53%	8.17%	9.86%	11.70%	12.41%	10.90%	11.13%	16.50%
upon divergence	Median	5.99%	7.37%	9.45%	11.20%	11.47%	9.96%	10.69%	14.96%
Return difference	Mean	3.70%	3.21%	4.07%	4.73%	4.24%	4.30%	4.18%	5.91%
at day of divergence	Median	2.88%	2.40%	3.30%	3.69%	3.00%	3.34%	3.07%	4.46%
No. industry group comb.		41	45	44	42	42	44	36	45
Max. industry group weight	Fraction	11.55%	13.98%	13.39%	12.40%	14.96%	21.29%	19.20%	24.82%
	Industries	Industrials and Financials	Cons. Discretionary and Financials	Industrials and and Financials	Industrials Cons. Discretionary	Health Care and Financials	Con. Discretionary and Financials	Industrials and Financials	Industrials and Financials
Industry group concentration		6.61%	6.00%	6.71%	6.29%	8.31%	9.26%	7.83%	13.05%

Table 6.10: Transition Matrix: Baseline Distraction Proxy Decile Ranks and Modified Ranks Available in Real Time

This table shows the transition matrix for baseline distraction proxy decile ranks and modified decile ranks, which are based on rolling historical raw proxy data. Specifically, for a given day, we use the preceding 250 trading days to compute the distraction decile the day belongs to. This implies that the beginning of the sample period is one year later (January 1963) than in the baseline case. Computations are based on all 102,259 sample pair trades, which are opened between January 1963 and December 2008. This implies that distraction proxy ranks at days where more (less) pairs diverge have a stronger (weaker) impact on the results displayed.

		Modified distraction proxy based on rolling historical data										
	Decile rank	1	2	3	4	5	6	7	8	9	10	Total
	1	64.55%	17.04%	4.82%	1.67%	0.97%	0.49%	0.21%	0.00%	0.00%	0.00%	7.91%
	2	21.02%	42.55%	18.31%	8.68%	5.55%	2.36%	0.81%	0.44%	0.13%	0.00%	8.38%
	3	8.32%	19.41%	36.20%	18.91%	9.46%	8.04%	3.06%	0.95%	0.42%	0.00%	8.83%
	4	4.49%	8.52%	18.25%	33.55%	15.57%	11.03%	7.14%	4.14%	1.28%	0.11%	9.07%
Baseline	5	1.41%	6.03%	8.13%	17.98%	35.40%	17.63%	12.46%	7.23%	2.39%	0.35%	9.70%
	6	0.20%	4.88%	5.87%	6.71%	17.58%	31.48%	17.18%	12.82%	4.99%	1.48%	9.73%
	7	0.00%	1.33%	5.62%	6.60%	5.89%	16.81%	31.62%	21.47%	10.93%	2.46%	10.26%
	8	0.00%	0.23%	1.92%	4.30%	5.64%	7.35%	17.31%	31.14%	24.39%	6.93%	10.70%
	9	0.00%	0.00%	0.89%	1.40%	3.46%	3.52%	7.34%	16.73%	42.47%	21.69%	11.82%
	10	0.00%	0.00%	0.00%	0.20%	0.49%	1.29%	2.88%	5.08%	12.99%	66.97%	13.60%
	Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 6.11: Multivariate Analysis: Investor Distraction (Real-Time Availability) and Returns on Pairs Trading

This table displays findings from pooled multivariate regressions of the one-month return on zero-cost US stock pairs on a proxy for investor distraction and up to three sets of control variables. The proxy for investor distraction is the *Distraction Proxy Decile Rank* (specifications 1-4) or a *High/Low Distraction Dummy* (specifications 5-8), which is zero for low distraction days (decile 1) and one for high distraction days (decile 10). In contrast to the baseline analysis in the paper, decile ranks are now constructed on the basis of rolling historical data to assure availability in real time. Specifically, for a given day, we use the preceding 250 trading days to compute the distraction decile the day belongs to. Pairs trading returns are computed under the conservative "one day waiting" return scheme. The first set of explaining variables controls for calendar and industry effects (indicator variables for year, month, day of week, and pair industry group combinations). The second set controls for market-level conditions on the day of divergence (market return, squared market return, market turnover, 10 day rolling volatility, factors for daily return premia on size, value, momentum and short-term reversal). The third set controls for a number of pair characteristics computed as outlined in table 3.1 (average firm market capitalization decile rank, ln (average pre-event turnover), ln (average pre-event Amihud illiquidity ratio), average idiosyncratic risk, within-pair differences in these variables, return difference attributable to the day of divergence, ln (average turnover on day of divergence) and ln (difference in turnover on day of divergence)). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

Model specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample period	1/1963-12/2008	1/1963-12/2008	7/1963-12/2008	7/1963-12/2008	1/1963-12/2008	1/1963-12/2008	7/1963-12/2008	7/1963-12/2008
Observations	101,539	101,539	100,426	99,673	25,963	25,963	25,705	25,538
Adjusted R^2	0.05%	2.63%	2.74%	2.84%	0.30%	5.02%	5.30%	5.36%
Distraction Proxy Decile Rank	0.00052***	0.00067***	0.00045***	0.00050***				
	(0.000109)	(0.000110)	(0.000119)	(0.000120)				
High/Low Distraction Dummy					0.00559***	0.00839***	0.00660***	0.00729***
					(0.001312)	(0.001486)	(0.001615)	(0.001650)
Controls for calender and industry effects	no	yes	yes	yes	no	yes	yes	yes
Controls for market-level conditions	no	no	yes	yes	no	no	yes	yes
Controls for pair characteristics	no	no	no	yes	no	no	no	yes

Table 6.12: The Impact of Time-Varying Arbitrage Risk and Investor Distraction on Pairs Trading Profitability

This table displays findings from pooled regressions of the one-month return on zero-cost US stock pairs on the proxy for investor distraction and/or the Chicago Board Options Exchange Market Volatility Index (VIX) over the period from January 1990 to December 2008. The proxy for investor distraction is the *Distraction Proxy Decile Rank* (specifications 3,5,6) or a *High/Low Distraction Dummy* (specifications 4,7,8), which is zero for low distraction days (decile 1) and one for high distraction days (decile 10). With regard to the VIX, we either use its raw value (specifications 1,5,7) or its decile ranks, computed separately for each year (specifications 2,6,8). Pairs trading returns are computed under the conservative "one day waiting" return scheme. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

Model specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample period	1/1990-12/2008	1/1990-12/2008	1/1990-12/2008	1/1990-12/2008	1/1990-12/2008	1/1990-12/2008	1/1990-12/2008	1/1990-12/2008
observations	39,666	39,666	39,666	8,372	39,666	39,666	8,372	8,372
Adjusted R^2	0.12%	0.15%	0.10%	0.30%	0.17%	0.18%	0.48%	0.52%
VIX (Raw Value)	0.00028***				0.00023***		0.00011	
	(0.000079)				(0.000081)		(0.000124)	
VIX (Yearly Decile Ranks)		0.00095***				0.00078***		0.000708*
		(0.000180)				(0.000187)		(0.000403)
Distraction Proxy Decile Rank			0.00079***		0.00060***	0.00053***		
			(0.000177)		(0.000177)	(0.000184)		
High/Low Distraction Dummy				0.01070***			0.009790***	0.00832***
				(0.002210)			(0.002221)	(0.002430)

Table 6.13: Further Tests (II): Investor Distraction and Pairs Trading Profitability

Panel A shows the sensitivity of pairs trading returns to distraction proxy decile ranks (as observed on the day of divergence) for several samples of top pairs: The monthly top 100 pairs each consisting of firms from different industries, the monthly top 100 pairs each consisting of firms from the same industries, and the monthly top 20 pairs each consisting of two value-weighted industries. In all cases, we use the Fama/French (1997) classification with 49 industries. The first column shows the return difference between pairs diverging on high distraction days (decile 10) and pairs diverging on low distraction days (decile 1). The approach resembles the methodology used in table 3.2. The second column shows findings from regressing pairs returns on the distraction proxy decile rank. Panel B reports results from a test similar in spirit. It compares the return sensitivity for pairs whose constituent firms share (do not share) at least one business segment, as described in detail in the text. Panel C compares returns from pairs consisting only of firms with high residual media coverage and pairs consisting only of firms with low residual media coverage, as described in detail in the text. The first column compares average event-time one-month pairs trading returns. The second column shows findings from regressing pairs returns on the distraction proxy decile rank. In all panels, statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Standard errors (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence.

Panel A: Impact of Investor Distraction on Pairs Consisting of Alternative Assets			
	Return computation	Diff.: Decile 10-Decile 1	Distraction Decile Rank
Top 100 pairs with stocks	no waiting	0.0101***	0.00089***
from different industries (N=103,386)		(0.00151)	(0.0000726)
Top 100 pairs with stocks		0.0094***	0.00083***
from the same industry (N=100,726)		(0.00156)	(0.0001154)
Top 20 industry-level pairs		0.0047**	0.00036**
(N=14,180)		(0.00190)	(0.0001451)
Panel B: Pairs With and Without Common Industry Segments (since 1977)			
	Return computation	Diff.: Decile 10-Decile 1	Distraction Decile Rank
No shared industry segment	no waiting	0.0115***	0.00096***
		(0.0024)	(0.00019)
Shared industry segment		0.0112***	0.00043
		(0.0039)	(0.00030)
Difference		0.00022	0.00053*
		(0.0039)	(0.00030)
Panel C: Pairs with High and Low Residual Media Coverage			
	Return computation	Return: All Deciles	Distraction Decile Rank
Low residual media coverage	no waiting	0.0108***	0.0011**
		(0.0017)	(0.0005)
High residual media coverage		0.0003	-0.0010
		(0.0030)	(0.0011)
Difference		0.0106***	0.0021*
		(0.0035)	(0.0012)

6.3 Appendix to Chapter 4

This appendix provides information that supplements the analysis in chapter 4. Table 6.14 shows time-series statistics of weekly return deviations of twin stocks. Table 6.15 provides cross-sectional statistics of deviations from theoretical price parity. Table 6.16 shows the impact of investor distraction on the level of price deviations from theoretical parity. Table 6.17 explores the impact of modified distraction proxies on return deviations of twin stocks. Tables 6.18 and 6.19 show results from baseline regressions with a lagged dependent variable on the right hand side.

Table 6.14: Descriptive Statistics of Absolute Weekly Return Deviations: Time Series Perspective

This table shows descriptive statistics of weekly return differences between twin stocks by sample year. Return deviations are computed as the absolute value of the difference between the currency-adjusted weekly log returns of the twins. Weekly returns are overlapping and constructed as rolling cumulative log returns over the previous five trading days. The minimum and maximum number of available DLCs ($No.DLCs$), their average absolute return difference, the corresponding standard deviation (StDev), the median, selected percentiles (P10, P50, P90), as well as the minimum (Min) und Maximum (Max) value are displayed for each year separately.

Year	No. DLCs	Mean	StDev	P10	P50	P90	Min	Max
1991	2-3	1.27%	0.58%	0.58%	1.21%	2.00%	0.15%	4.47%
1992	2-3	1.18%	0.61%	0.49%	1.12%	1.91%	0.13%	4.40%
1993	2-5	1.35%	0.52%	0.72%	1.30%	2.06%	0.37%	2.98%
1994	5-6	1.25%	0.38%	0.77%	1.25%	1.72%	0.37%	2.58%
1995	5-7	1.06%	0.35%	0.67%	1.02%	1.49%	0.27%	2.36%
1996	6-7	1.23%	0.41%	0.73%	1.18%	1.77%	0.35%	2.77%
1997	7-8	1.54%	0.55%	0.87%	1.49%	2.20%	0.47%	4.12%
1998	8-9	1.78%	0.61%	1.11%	1.70%	2.51%	0.51%	4.06%
1999	6-9	1.88%	0.67%	1.13%	1.78%	2.89%	0.67%	4.09%
2000	4-6	1.98%	0.83%	1.02%	1.91%	3.15%	0.30%	5.20%
2001	4-6	1.91%	0.91%	0.88%	1.75%	3.13%	0.35%	5.00%
2002	6-6	1.99%	0.93%	0.99%	1.81%	3.26%	0.43%	6.15%

Table 6.15: Deviations from Theoretical Price Parity: Cross-Sectional Perspective

This table shows characteristics of the logarithmized price deviations from theoretical price parity for dual-listed companies. *Time Diff* refers to the time differential (in hours) between the two countries in which the twin stocks are primarily traded. *Abs. Value* refers to the the average absolute deviation, StDev to the standard deviation, and % pos to the fraction of positive values.

ID	DLC	Time Diff	Sample Start	Sample Ende	Abs. Value	Mean	StDev	Minimum	Maximum	% pos
1	Royal Dutch	-1	2-Jan-91	3-Oct-02	8.43%	8.16%	4.98%	-5.26%	19.83%	91.75%
2	Unilever	-1	2-Jan-91	3-Oct-02	7.27%	5.57%	6.68%	-10.51%	25.85%	72.35%
3	ABB	0	3-Jan-94	7-Jan-99	8.43%	8.15%	5.29%	-5.58%	17.77%	92.44%
4	Smithkline	-5	2-Jan-91	22-Jan-96	7.95%	7.75%	4.45%	-2.23%	15.97%	90.77%
5	Fortis	0	4-Jan-93	31-Jul-00	4.10%	-2.06%	4.61%	-17.03%	12.78%	32.84%
6	Elsevier	-1	4-Jan-93	3-Oct-02	8.88%	2.15%	9.20%	-14.73%	17.58%	55.58%
7	Rio Tinto	-10	21-Dec-95	3-Oct-02	4.11%	-1.90%	4.76%	-16.42%	11.31%	37.44%
8	Dexia	0	19-Nov-96	20-Aug-99	9.43%	-9.37%	3.46%	-18.42%	4.31%	1.39%
9	Merita	-1	15-Dec-97	23-Aug-99	7.07%	-7.01%	3.19%	-15.11%	2.03%	3.17%
10	Zurich	-1	7-Sep-98	20-Mar-00	11.93%	11.93%	3.47%	1.36%	21.00%	100.00%
11	BHP	-10	29-Jun-01	3-Oct-02	7.09%	7.09%	2.26%	1.14%	18.45%	100.00%
12	Brambles	-10	7-Aug-01	3-Oct-02	11.32%	8.45%	11.32%	-18.62%	29.15%	74.26%
Pooled					7.42%	3.53%	7.94%	-18.62%	29.15%	64.59%

Table 6.16: Deviations from Theoretical Price Parity and Investor Distraction (Median Split)

This table compares the level of twin stock price deviations from theoretical parity during moments of high distraction with the level of deviations during moments of low distraction. Moments of *High* (*Low*) *Distraction* are defined as days (in panel A) or weeks (in panel B) during which the distraction proxy takes on values greater (smaller) than 11. *Absolute Change* denotes the percentage point change of price deviations between times of high distraction and times of low distraction. The row below displays the corresponding p-value. To control for heteroscedasticity and autocorrelation, standard errors in both panels are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively. *Relative Change* denotes the percent change of price deviations.

ID	1	2	3	4	5	6	7	8	9	10	11	12		
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled	Pooled
Sample Start	2-Jan-91	2-Jan-91	3-Jan-94	2-Jan-91	4-Jan-93	4-Jan-93	21-Dec-95	19-Nov-96	15-Dec-97	7-Sep-98	29-Jun-01	7-Aug-01	(firm-fixed	(no fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)	effects)
Daily Frequency														
Panel A: High Distraction (Decile 12 or larger) vs. Low Distraction (Decile 10 or smaller)														
N	2,682	2,682	1,123	1,149	1,736	2,225	1,558	628	380	357	283	258	15,061	15,061
High Distraction	8.66%	7.49%	8.53%	7.95%	3.99%	8.86%	4.44%	9.63%	6.94%	12.43%	7.21%	12.15%	11.33%	7.57%
Low Distraction	8.12%	7.02%	8.19%	7.90%	4.09%	8.81%	3.91%	9.27%	7.28%	11.12%	7.09%	10.38%	11.00%	7.22%
Absolute Change	0.53%**	0.47%*	0.34%	0.05%	-0.09%	0.05%	0.53%**	0.37%	-0.34%	1.31%***	0.12%	1.77%	0.33%***	0.35%***
P-value	0.040	0.082	0.387	0.885	0.605	0.782	0.012	0.344	0.442	0.004	0.769	0.306	0.001	0.001
Relative Change	6.57%	6.71%	4.18%	0.61%	-2.28%	0.56%	13.55%	3.97%	-4.62%	11.82%	1.71%	17.06%	2.99%	4.88%
Weekly Frequency														
N	2,692	2,692	1,138	1,162	1,700	2,237	1,562	626	377	351	299	272	15,108	15,108
High Distraction	8.90%	7.69%	8.73%	8.02%	3.96%	8.82%	4.45%	9.89%	6.97%	13.03%	7.05%	12.03%	11.80%	7.69%
Low Distraction	7.96%	6.84%	7.92%	8.00%	4.17%	8.88%	3.82%	8.95%	7.07%	10.51%	7.08%	11.86%	11.30%	7.16%
Absolute Change	0.94%**	0.85%**	0.81%	0.02%	-0.21%	-0.06%	0.63%**	0.94%*	-0.10%	2.52%***	-0.04%	0.17%	0.50%***	0.53%***
P-value	0.016	0.036	0.183	0.967	0.477	0.837	0.028	0.067	0.864	0.000	0.926	0.853	0.001	0.001
Relative Change	11.81%	12.43%	10.20%	0.25%	-4.93%	-0.67%	16.48%	10.51%	-1.40%	23.98%	-0.50%	1.43%	4.40%	7.36%

Table 6.17: The Impact of Modified Investor Distraction Proxies on Twin Stock Return Differences: Pooled Regression Results

This table shows results from pooled regressions of return deviations on (modified) proxies for investor distraction as well as on several control variables, as described in detail in the text. Return deviations are computed as the absolute value (in basis points) of the difference between the currency-adjusted daily or weekly log returns of the twins. All regressions are run with firm-fixed effects. *Weighting scheme* refers to the way domestic market industry-level shocks are aggregated (see the text for details). HD/LD is short for high (low) distraction. In the last row, *Predicted sign* denotes how many of the in total five distraction coefficients obtain the predicted sign. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

Weighting Scheme	Value-weighting market segments				Equal-weighting market segments			
Frequency	Daily	Daily	Weekly	Weekly	Daily	Daily	Weekly	Weekly
Regression framework	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Panel A: Distraction Proxy Set 1								
HD Proxy	2.71***	1.58***	3.44***	2.45***	2.62***	1.58***	3.56***	2.70***
	(11.63)	(7.97)	(9.32)	(7.27)	(11.74)	(8.21)	(9.46)	(7.95)
P-Value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Adj. R^2	0.13	0.19	0.14	0.17	0.13	0.19	0.14	0.17
Panel B: Distraction Proxy Set 2								
HD Dummy	25.22***	13.01***	32.6***	19.67***	18.20***	8.29***	32.35***	19.99***
	(9.21)	(5.53)	(-7.50)	(4.91)	(7.21)	(3.64)	(7.10)	(4.91)
LD Dummy	-7.78***	-5.48***	-10.97***	-11.69***	-11.49***	-8.47***	-13.77***	-14.16***
	(-4.10)	(-2.93)	(-3.47)	(-4.97)	(-6.37)	(-4.78)	(-4.44)	(-4.97)
P-value joint sign.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Adj. R^2	0.13	0.19	0.14	0.17	0.12	0.19	0.14	0.18
Panel C: Distraction Proxy Set 3								
HD Dummy	34.26***	13.79***	56.82***	36.67***	32.50***	12.17***	47.56***	29.00***
	(6.97)	(3.14)	(7.45)	(7.39)	(6.91)	(2.93)	(5.95)	(4.07)
LD Dummy	-15.08***	-10.29***	-17.83***	-18.33***	-16.76***	-12.71***	-16.67***	-17.65***
	(-5.47)	(-3.77)	(-4.17)	(-4.24)	(-5.95)	(-4.52)	(-3.80)	(-4.02)
P-value joint sign.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Adj. R^2	0.12	0.19	0.14	0.17	0.12	0.19	0.14	0.17
Predicted Sign	5/5	5/5	5/5	5/5	5/5	5/5	5/5	5/5

Table 6.18: Daily Return Deviations and Investor Distraction: Multivariate Tests with Lagged Dependent Variable

This table shows results from multivariate regressions of the absolute difference (in basis points) of daily currency-adjusted log returns on proxies for investor distraction as well as on several control variables, as described in detail in the text. Additionally, a lagged dependent variable is included on the right-hand side. Regressions are run separately for each DLC as well as for the pooled sample with firm-fixed effects (last column). HD/LD is short for high (low) distraction. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). DAH denotes the average p-value obtained from Durbin's Alternate H. *Predicted sign* denotes how many of the in total five distraction coefficients obtain the sign predicted by our hypotheses. Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Sample Start	2-Jan-91	2-Jan-91	3-Jan-94	2-Jan-91	4-Jan-93	4-Jan-93	21-Dec-95	19-Nov-96	15-Dec-97	7-Sep-98	29-Jun-01	7-Aug-01	(firm-fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)
Panel A: Distraction Proxy Set 1													
HD Proxy	1.12***	2.51***	0.47	0.71*	1.21***	1.36***	2.75***	1.12	-0.08	0.76	0.35	4.42	1.55***
	(4.05)	(5.44)	(0.84)	(1.69)	(2.70)	(3.52)	(2.62)	(1.11)	(-0.05)	(0.53)	(0.13)	(1.31)	(7.80)
P-Value	0.000***	0.000***	0.403	0.091*	0.007***	0.000***	0.009***	0.266	0.957	0.596	0.895	0.190	0.000***
Panel B: Distraction Proxy Set 2													
HD Dummy	9.77***	8.83	10.05	-0.65	5.81	7.32	28.59**	13.71	-37.82**	-6.90	38.32	78.80**	10.05***
	(2.79)	(1.57)	(1.60)	(-0.12)	(1.02)	(1.48)	(2.14)	(1.19)	(-2.25)	(-0.50)	(1.02)	(2.00)	(4.07)
LD Dummy	-5.39**	-18.71***	0.05	-6.81	-7.44	-7.36*	-7.06	2.70	-23.17*	7.63	25.63	-18.31	-8.22***
	(-2.17)	(-4.11)	(0.01)	(-1.64)	(-1.46)	(-1.85)	(-0.79)	(0.29)	(-1.80)	(0.46)	(0.97)	(-0.58)	(-4.40)
P-value joint sign.	0.0001***	0.000***	0.276	0.249	0.122	0.024**	0.061*	0.491	0.029**	0.769	0.427	0.087*	0.000***
Panel C: Distraction Proxy Set 3													
HD Dummy	9.79	6.61	6.32	2.49	3.61	5.46	44.94*	44.07*	-16.83	-16.29	82.10	67.53	13.17***
	(1.44)	(0.68)	(0.52)	(0.32)	(0.39)	(0.51)	(1.88)	(1.66)	(-0.73)	(-0.76)	(1.34)	(0.89)	(2.86)
LD Dummy	-7.58**	-27.31***	1.57	-16.19**	-0.13	-13.99**	-15.45	-1.61	-17.53	-35.03*	-35.01	-65.35	-13.46***
	(-1.97)	(-3.78)	(0.16)	(-2.54)	(-0.02)	(-2.48)	(-1.34)	(-0.10)	(-0.78)	(-1.73)	(-0.98)	(-1.51)	(-4.59)
P-value joint sign.	0.04**	0.000***	0.862	0.031**	0.926	0.033**	0.071*	0.252	0.569	0.159	0.274	0.205	0.000***
Predicted Sign	5/5	5/5	3/5	4/5	5/5	5/5	5/5	4/5	2/5	2/5	4/5	5/5	5/5
DAH	0.036**	0.764	0.051*	0.814	0.000***	0.004***	0.326	0.023**	0.524	0.288	0.364	0.366	
Lagged dep. var.	0.18***	0.19***	0.05	0.17***	0.16***	0.15***	0.16***	0.10*	0.06	0.12**	0.09	0.08	0.16***
Mean Adj. R^2	0.14	0.15	0.13	0.06	0.08	0.17	0.16	0.07	0.06	0.00	0.04	0.10	0.22

Table 6.19: Weekly Return Deviations and Investor Distraction: Multivariate Tests with Lagged Dependent Variable

This table shows results from multivariate regressions of the absolute difference (in basis points) of weekly currency-adjusted log returns on proxies for investor distraction as well as on several control variables, as described in detail in the text. Additionally, a lagged dependent variable is included on the right-hand side. Regressions are run separately for each DLC as well as for the pooled sample with firm-fixed effects (last column). HD/LD is short for high (low) distraction. In panels B and C, p-values of joint significance are computed from Wald tests that the coefficients of both distraction dummies are zero. To control for heteroscedasticity and autocorrelation, t-statistics (in parentheses) in all panels are calculated with standard errors adjusted by the method of Newey and West (1987). *DAH* denotes the average p-value obtained from Durbin's Alternate H. *Predicted sign* denotes how many of the in total five distraction coefficients obtain the sign predicted by our hypotheses. Statistical significance at the ten, five and one-percent levels is indicated by *, **, and ***, respectively.

ID	1	2	3	4	5	6	7	8	9	10	11	12	
DLC	Royal Dutch	Unilever	ABB	Smithkline	Fortis	Elsevier	Rio Tinto	Dexia	Merita	Zurich	BHP	Brambles	Pooled
Sample Start	3-Apr-91	3-Apr-91	5-Apr-94	3-Apr-91	1-Apr-93	1-Apr-93	25-Mar-96	20-Feb-97	18-Mar-98	7-Dec-98	28-Sep-01	5-Nov-01	(firm-fixed
Sample End	3-Oct-02	3-Oct-02	7-Jan-99	22-Jan-96	31-Jul-00	3-Oct-02	3-Oct-02	20-Aug-99	23-Aug-99	20-Mar-00	3-Oct-02	3-Oct-02	effects)
Panel A: Distraction Proxy Set 1													
HD Proxy	1.39***	1.76***	0.41	0.29	1.16*	1.79***	2.51**	1.23	0.93	2.42	7.13***	5.37	1.64***
	(3.89)	(3.34)	(0.57)	(0.50)	(1.76)	(3.15)	(2.03)	(0.99)	(0.52)	(1.19)	(3.24)	(0.93)	(6.58)
P-Value	0.000***	0.001***	0.568	0.617	0.078*	0.002***	0.042**	0.322	0.600	0.234	0.001***	0.355	0.000***
Panel B: Distraction Proxy Set 2													
HD Dummy	15.09***	5.41	2.59	5.59	-1.05	8.76	26.69*	17.26	33.08*	23.91	67.58**	75.41	12.86***
	(3.24)	(0.70)	(0.31)	(0.86)	(-0.14)	(1.23)	(1.78)	(1.36)	(1.68)	(1.01)	(2.02)	(1.07)	(4.06)
LD Dummy	-3.39	-13.25**	-7.65	7.91	-18.12***	-15.06***	-4.31	3.31	15.21	-11.56	-17.99	1.84	-7.80***
	(-0.97)	(-2.44)	(-1.07)	(1.33)	(-2.61)	(-3.20)	(-0.40)	(0.25)	(0.88)	(-0.54)	(-0.79)	(0.04)	(-3.34)
P-value joint sign.	0.002***	0.01***	0.509	0.335	0.027**	0.001***	0.165	0.389	0.149	0.420	0.037**	0.562	0.000***
Panel C: Distraction Proxy Set 3													
HD Dummy	8.19	8.64	5.85	2.95	27.62*	22.79	30.72	20.53	7.58	47.48	28.06	113.85	19.26***
	(1.22)	(0.91)	(0.37)	(0.20)	(1.85)	(1.64)	(1.04)	(1.04)	(0.36)	(1.04)	(0.63)	(0.71)	(3.26)
LD Dummy	-5.33	-17.65**	11.03	-7.06	-18.80	-14.14**	-25.66	1.10	-23.63	-45.82	-46.38**	15.38	-12.82***
	(-1.28)	(-2.52)	(1.11)	(-0.84)	(-1.56)	(-2.33)	(-1.56)	(0.05)	(-1.40)	(-1.19)	(-2.30)	(0.21)	(-3.60)
P-value joint sign.	0.182	0.018**	0.516	0.683	0.049**	0.014**	0.179	0.583	0.352	0.273	0.061*	0.759	0.000***
Predicted Sign	5/5	5/5	4/5	4/5	4/5	5/5	5/5	3/5	4/5	5/5	5/5	3/5	5/5
DAH	0.000***	0.000***	0.53	0.002***	0.723	0.091*	0.076*	0.834	0.089*	0.397	0.265	0.026**	
Lagged dep. var.	0.38***	0.32***	0.35***	0.23***	0.44***	0.23***	0.17***	0.24***	0.28***	0.40***	0.06	0.50***	0.32***
Mean Adj. R^2	0.22	0.17	0.15	0.07	0.26	0.22	0.09	0.08	0.09	0.23	0.11	0.27	0.26

6.4 Appendix to Chapter 5

This appendix provides information that supplements the analysis in chapter 5. Table 6.20 reports factor loadings from a Carhart (1997) four factor model for every portfolio strategy under consideration. Talbe 6.21 reports factor loading from a three factor market model. Finally, this appendix provides detailed information about the calculation of size, value, and momentum factors relied on.

Table 6.20: Markowitz vs. Heuristics: International Stock Market Diversification Results for a Carhart Four Factor Model

This table documents the results from regressing portfolio excess returns on the world factor returns ERM, SMB, HML and WML. ERM is the excess return of the value-weighted global stock index. SMB is the return difference between small and large capitalization stocks, HML is the return difference between stocks with high and low book-to-market ratios and WML is the return difference between stocks with high and low past stock returns. This table reports alphas (α^{4F}), betas and the adjusted R^2 for the international equity portfolios which are constructed using the various Markowitz-based optimization models and heuristic models. All values are reported for the total sample period (1973-2009). T-statistics are reported in parentheses. We assume a bid-ask spread of 40 basis points to calculate after-cost returns.

Portfolio Model	α^{4F}	β^{ERM}	β^{SMB}	β^{HML}	β^{WML}	Adj. R^2
Panel A: Markowitz-based Optimization Models						
maxsr	0.24%	1.05	-0.02	0.09	-0.06	73.6%
	(1.58)	(33.30)	(-0.30)	(1.44)	(-1.50)	
minvar$_n b$	-0.03%	0.89	-0.02	0.14	0.02	84.3%
	(-0.37)	(47.11)	(-0.73)	(3.77)	(0.96)	
minvar	0.04%	0.93	0.01	0.11	0.02	91.4%
	(0.57)	(65.76)	(0.58)	(3.86)	(0.89)	
js	0.13%	0.95	-0.01	0.08	-0.07	79.1%
	(1.11)	(38.65)	(-0.22)	(1.67)	(-2.21)	
js$_c cm$	0.15%	0.95	-0.03	0.07	-0.08	78.8%
	(1.22)	(38.11)	(-0.59)	(1.32)	(-2.75)	
ccm$_m axsr$	0.19%	1.02	-0.03	0.07	-0.07	75.0%
	(1.33)	(34.32)	(-0.64)	(1.15)	(-2.01)	
ccm$_m invar$	0.05%	0.93	0.00	0.10	-0.01	91.1%
	(0.65)	(64.51)	(0.14)	(3.54)	(-0.61)	
nc1v	-0.02%	0.90	-0.02	0.14	0.02	85.2%
	(-0.21)	(48.71)	(-0.62)	(3.70)	(0.89)	
nc1r	0.03%	0.93	-0.02	0.13	0.02	89.6%
	(0.43)	(59.69)	(-0.76)	(4.29)	(1.18)	
nc2v	-0.02%	0.92	0.00	0.13	0.02	89.7%
	(-0.24)	(59.80)	(0.14)	(4.18)	(1.03)	
nc2r	0.02%	0.93	-0.01	0.13	0.02	90.8%
	(0.26)	(63.59)	(-0.31)	(4.26)	(1.21)	
Panel B: Heuristic Models						
60-25-15; gdp	0.08%	0.99	0.07	0.05	-0.01	95.7%
	(1.57)	(94.05)	(3.72)	(2.42)	(-0.44)	
60-25-15; macap	0.00%	1.00	0.00	0.00	0.00	100.0%
	(0.00)	(97.23)	(0.00)	(0.00)	(0.00)	
60-25-15; naiv	0.08%	0.99	0.07	0.06	0.00	95.1%
	(1.46)	(88.42)	(3.61)	(2.87)	(-0.04)	

Table 6.21: Markowitz vs. Heuristics: Asset Allocation Results from a Three Factor Model

This table documents the results from regressing portfolio excess returns on a three factor model comprising of excess returns on the stock, bond and commodity market, respectively. This table reports alphas (α^{3F}), betas and the adjusted R^2 for the asset allocation portfolios which are constructed using the various Markowitz-based optimization models and heuristic models. T-statistics are reported in parentheses. All values are reported for the subsample period from 1988-2009. We assume a bid-ask spread of 40 basis points to calculate after-cost returns.

Portfolio Model	α^{3F}	β^{Stocks}	β^{Bonds}	$\beta^{Commodities}$	Adj. R^2
Panel A: Markowitz-based Optimization Models					
maxsr	-0.09%	0.40	1.06	0.03	50.60%
	(-0.64)	(13.88)	(7.60)	(1.31)	
minvar-nb	-0.02%	0.00	0.92	0.04	82.40%
	(-0.75)	(0.63)	(35.04)	(9.59)	
minvar	0.01%	0.03	0.92	0.03	92.80%
	(-0.43)	(10.00)	(56.77)	(12.54)	
js	-0.09%	0.15	0.86	0.14	44.60%
	(-0.86)	(7.16)	(8.37)	(7.92)	
js-ccm	-0.02%	0.26	0.89	0.15	49.20%
	(-0.12)	(10.32)	(7.37)	(7.17)	
ccm-maxxsr	-0.28%	0.41	0.91	0.09	54.80%
	(-2.06)	(14.77)	(6.75)	(3.86)	
ccm-minvar	0.00%	0.06	0.95	0.02	97.20%
	(0.44)	(25.75)	(91.51)	(12.79)	
nc1v	-0.02%	0.00	0.91	0.04	82.70%
	(-0.67)	(0.79)	(35.38)	(9.66)	
nc1r	0.01%	0.03	0.92	0.03	92.50%
	(0.54)	(9.75)	(55.87)	(12.34)	
nc2v	-0.02%	0.02	0.92	0.04	87.60%
	(-0.83)	(4.39)	(42.75)	(10.23)	
nc2r	0.01%	0.03	0.92	0.03	92.80%
	(0.43)	(10.00)	(56.77)	(12.54)	
Panel B: Heuristic Models					
60-25-15; GDP	0.12%	0.60	0.21	0.18	96.40%
	(2.86)	(71.30)	(5.09)	(25.70)	
60-25-15; macap	0.02%	0.59	0.26	0.16	99.60%
	(1.18)	(227.86)	(20.82)	(75.47)	
60-25-15; naiv	0.10%	0.60	0.21	0.18	96.50%
	(2.45)	(71.57)	(5.23)	(26.03)	

Data selection for the stock universe Security data is extracted from Thomson Reuters Datastream. For each stock market of interest, we create a constituent list based on all securities which belong to that market and are coded as TYPE "Equity" or "Preference Share". Securities are included independent of their status ("Active", "Dead" or "Suspended"). We construct constituent lists for the following Datastream markets: Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Portugal, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, and United Kingdom. These are all countries/markets that are either used for the construction of the MSCI regional benchmark indices MSCI Europe, MSCI Euro-Zone, MSCI North America, MSCI Pacific, or comprise the G-20 group of the world's largest economies. Exceptions are Saudi Arabia, for which no data is available from Datastream, and the United States, for which we can obtain factor returns from Kenneth French's website.[1] Our procedure results in a total sample of 47,130 unique securities. We then make use of the Datastream security identifier (DSCD) to download the following data for our sample: International Securities Identification Number (ISIN), geographical status (GEOGN), total return index (RI), unadjusted price (UP), Datastream total market value of equity (MV), Worldscope total market capitalization at fiscal year end (WC08001), and Worldscope book value of equity at fiscal year end (WC03501). All numerical values are converted in Euro. We use the variable GEOGN to identify and exclude firms which are assigned to the wrong stock market. All firms having either no stock data (no values for RI or UP) or no Worldscope data (no values for WC08001 or WC03501) are dropped from the sample. Security returns are calculated using the total return index (RI) which is adjusted for dividends (i.e. assumes that dividends are re-invested) and stock splits. To clean the return data, we apply the following screens advocated by Ince and Porter (2006). First, each month we identify firms that have been delisted previously. Second, firm observations are classified as penny stocks whenever their unadjusted price (UP) was in the lowest decile in more than 50% of the last twelve months. Third, we remove unrealistic returns from the data by setting any return above 300% that is reversed within one month to missing.

[1]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Factor construction for individual stock markets Factors are constructed separately for each stock market. We follow the methodology outlined on Kenneth French's website. In particular, in order to construct the value and size factors, we form six value-weighted portfolios based on firm size and equity book-to-market ratio each year at the end of June. A firm's equity book-to-market ratio for June is defined as WC03501/WC08001 using values at the end of the firm's fiscal year ending anywhere in the previous calendar year. Firm size for June is the total market value of equity (MV) at the end of June. To be included in any of the portfolios, we impose the following requirements: 1) the firm's stock must have valid price data at the end of June (i.e. no previous delisting and no penny stock), and 2) neither WC03501 nor WC08001 nor MV must be negative. We use the same breakpoints as Fama and French (1993) to sort stocks into the portfolios, i.e. the breakpoints for the book-to-market ratio are the 30th and 70th percentiles and the size breakpoint is the median market equity. Returns for the size factor (SMB) and value factor (HML) are then calculated as follows:

$$\begin{aligned} SMB = & \frac{1}{3} \cdot (Small\,Value + Small\,Neutral + Small\,Growth) \\ & -\frac{1}{3} \cdot (Big\,Value + Big\,Neutral + Big\,Growth). \end{aligned} \tag{6.1}$$

$$HML = \frac{1}{2} \cdot (Small\,Value + Big\,Value) - \frac{1}{2} \cdot (Small\,Growth + Big\,Growth). \tag{6.2}$$

The momentum factor is computed based on six value-weighted portfolios formed on total market equity (MV) at the end of the previous month and prior 1-year return (excluding the return of the most recent month). In contrast to the value and size factor-mimicking portfolios, the momentum portfolios are rebalanced monthly. Return breakpoints are the 30th and 70th percentiles and the size breakpoint is the median market equity. 1) Invalid price data, 2) negative MV data, or 3) missing prior one-year return data results in exclusion of the firm's stock for the particular month concerned. Returns for the momentum factor (WML) are then calculated as follows:

$$WML = \frac{1}{2} \cdot (Small\,High + Big\,High) - \frac{1}{2} \cdot (Small\,Low + Big\,Low). \tag{6.3}$$

Construction of regional stock market factors

In order to compute the world-wide factors and the factors for the different world regions comprising of several markets/countries, we utilize the methodology of Griffin (2002). That is, world-wide respectively regional factors are market weighted averages of the country-specific components. For example, the value factor for Europe in month t is calculated as: $HML_{t,Eur} = \sum_{k=1}^{N} I_{k,t,Eur} \cdot w_{k,t-1,Eur} \cdot HML_{k,t}$, where N is the total number of countries, $I_{k,t,Eur}$ is an indicator variable taking the value 1 (0) when country k is a part of Europe, $w_{k,t-1,Eur}$ is the fraction of the total dollar-denominated European market capitalization attributable to country k at the end of the previous month, and $HML_{k,t}$ is the factor-mimicking return for country k in month t. Data on the total dollar-market capitalization of each country is extracted from Datastream (e.g., code TOTMKBD(MV) for Germany). Our assignment of the countries to the regions Europe, European Monetary Union, North America, and Pacific follows the index country membership definition used by MSCI. To construct the world factors, we use a slightly different methodology: Each month, we sort countries in descending order based on their total dollar-denominated market capitalization and calculate the cumulative coverage of the world market capitalization at each country. After a total market coverage of 85% is achieved, we stop with this procedure and exclude all other countries from the factor return calculations. Market weights for the included countries are adjusted proportionally. With this approach, we account for the fact that errors in the database are more likely for firms in smaller, emerging economies, especially in the earlier parts of the sample period. Since our sample period is from 1973 till 2009 in chapter 5, but Worldscope data is not available prior to 1980, we use the U.S. factor returns from Kenneth French's website for the earlier part of our sample period (1973-1980) as an approximation for the world-wide factor returns. The dollar-market capitalization weight of the United States was considerably larger in the 1970's than in the later parts of the sample period. Hence, we do not expect this methodology to have an fundamental impact on the estimated factor returns.

Data selection for the bond and commodity universe All of our bond and commodity data are extracted from Thomson Reuters Datastream. Specifically, our selection of 21 commodities comprises GSCI total return indices as well as spot prices for Aluminum, Brent Crude, Cocoa, Coffee, Copper, Corn, Cotton, Crude Oil, Gas Oil, Gold, Heating Oil, Lead, Live Cattle, Lean Hogs, Natural Gas, Nickel, Silver, Soybeans, Sugar, Wheat, and Zinc. At any point in time during our sample period for this analysis (January 1988 to December 2009), data on at least 14 commodities are available. Our bonds selection constitutes of Merrill Lynch short-term government bond index returns as well as five-year government bond yields for the following nine countries: Australia, Canada, Denmark, Germany, Japan, Norway, Sweden, Switzerland, United Kingdom, United States. Asness et al. (2009) rely on the same countries (plus Norway). At any point in time during our sample period, at least seven bond series are available. Finally, we also obtain changes in country-specific consumer price index changes for all of these countries.

Factor construction for the bond and commodity market Our methodology is intended to result in simple value and momentum measures for bonds and commodities, which are, to the extent possible, consistent with the basic ideas developed in the recent literature. To this end, we closely follow the concept employed by Asness et al. (2009) in deriving our value measures for commodities and bonds. Specifically, for commodities, the measure for month t is computed as the spot price five years ago divided by the spot price in month t-2. For bonds, the value measure is computed as the yield on the five-year government bond index minus the current change in the county-specific consumer price index. The latter might be regarded as a proxy for rational inflation expectations. For momentum, we follow an approach commonly employed in studies on the stock market. Specifically, our momentum measure is the past cumulative (total) return on the asset during months t-12 to t-2. For both bonds and commodities, we construct zero-cost, long-short portfolios. To this end, we first compute, for any point in time, the median of the measures for value and momentum. Each component of the bond or commodity universe with a value above or below this breakpoint is then assigned to either the long or the short portfolio. Components are equal-weighted. This portfolio construction is redone every month. The factor return for month t is then simply computed as the difference between the return of the long portfolio and the return of the short portfolio.

Bibliography

Abreu, D., and M. K. Brunnermeier, 2002, "Synchronization risk and delayed arbitrage," *Journal of Financial Economics*, 66, 341–360.

Agnew, J., P. Balduzzi, and A. Sunden, 2003, "Portfolio choice and trading in a large 401(k) plan," *American Economic Review*, 93, 193–215.

Ai, C., and E. C. Norton, 2003, "Interaction terms in logit and probit models," *Economic Letters*, 80, 123–129.

Amihud, Y., 2002, "Illiquidity and stock returns: Cross-section and time-series effects," *Journal of Financial Markets*, 5, 31–56.

Amin, G. S., and H. M. Kat, 2003, "Stocks, bonds and hedge funds: Not a free lunch!," *Journal of Portfolio Management*, 29, 113–120.

Andrade, S. C., V. di Pietro, and M. S. Seasholes, 2005, "Understanding the profitability of pairs trading," *Unpublished working paper, U.C. Berkeley, Northwestern University.*

Annaert, J., M. J. D. Ceuster, and W. V. Hyfte, 2005, "The value of asset allocation advice: Evidence from the Economist's quarterly portfolio poll," *Journal of Banking and Finance*, 29, 661–680.

Anson, M. J., 1999, "Maximizing utility with commodity futures diversification," *Journal of Portfolio Management*, 25, 86–94.

Arnott, R. D., J. Hsu, and P. Moore, 2005, "Fundamental indexation," *Financial Analysts Journal*, 61, 83–99.

Arshanapalli, B., T. D. Coggin, and W. Nelson, 2001, "Is fixed-weight asset allocation really better?," *Journal of Portfolio Management*, 27, 27–38.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen, 2009, "Value and momentum everywhere," *Unpublished working paper, AQR Capital Management, University of Chicago, New York University.*

Avramov, D., T. Chorida, and A. Goyal, 2006, "Liquidity and autocorrelations in individual stock returns," *Journal of Finance*, 61, 2365–2394.

Bagnoli, M., M. Clement, and S. G. Watts, 2006, "Around-the-clock media coverage and the timing of earnings announcements," *Unpublished working paper, McCombs Research Paper Series.*

Baik, B., J.-K. Kang, and J.-M. Kim, 2010, "Local institutional investors, information asymmetries, and equity returns," *Journal of Financial Economics*, 97, 81–106.

Bailey, W., A. Kumar, and D. Ng, 2008, "Foreign investments of U.S. individual investors: Causes and consequences," *Management Science*, 54, 443–459.

Barber, B. M., and T. Odean, 2000, "Trading is hazardous to your wealth," *Journal of Finance*, 55, 773–806.

——— , 2008, "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors," *Review of Financial Studies*, 21, 785–818.

——— , 2011, "The behavior of individual investors," *Unpublished working paper, University of California.*

Barberis, N., and A. Shleifer, 2003, "Style investing," *Journal of Financial Economics*, 68, 161–199.

Barberis, N., A. Shleifer, and J. Wurgler, 2005, "Comovement," *Journal of Financial Economics*, 75, 283–317.

Bedi, J., A. Richards, and P. Tennant, 2003, "The characteristics and trading behavior of dual-listed companies," *Unpublished working paper, Reserve Bank of Australia.*

Ben-David, I., F. Franzoni, and R. Moussawi, 2011, "Hedge fund stock trading in the financial crisis of 2007-2008," *Review of Financial Studies, forthcoming,.*

Benartzi, S., 2001, "Excessive extrapolation and the allocation of 401(k) accounts to company stock," *Journal of Finance*, 61, 1747–1764.

Benartzi, S., and R. Thaler, 2007, "Heuristics and biases in retirement savings behavior," *Journal of Economic Perspectives*, 21, 81–104.

Berger, P. G., and E. Ofek, 1995, "Diversification's effect on firm value," *Journal of Financial Economics*, 37, 39–65.

Biglova, A., S. Ortobelli, S. Rachev, and S. Stoyanov, 2004, "Different approaches to risk estimation in portfolio theory," *Journal of Portfolio Management*, 31, 103–112.

Black, F., 1986, "Noise," *Journal of Finance*, 41, 529–543.

Black, F., and R. Litterman, 1992, "Global portfolio optimization," *Financial Analysts Journal*, 48, 28–43.

Blake, D., B. N. Lehmann, and A. Timmermann, 1999, "Asset allocation dynamics and pension fund performance," *Journal of Business*, 72, 429–461.

Bodnaruk, A., 2009, "Proximity always matters: Local bias when the set of local companies changes," *Review of Finance*, 13, 629–656.

Boersch-Supan, A., M. Coppola, L. Essig, A. Eymann, and D. Schunk, 2009, "SAVE study - design and results," *Mannheim Research Institute for the Economics and Aging.*

Boyer, B. H., 2011, "Style related comovement: Fundamentals or labels?," *Journal of Finance*, 66, 307–332.

Brandt, M., A. Brav, J. R. Graham, and A. Kumar, 2010, "Idiosyncratic volatility puzzle: Time trend or speculative episodes?," *Review of Financial Studies*, 23, 863–899.

Brealey, R. A., S. C. Myers, and F. Allen, 2008, "Principles of corporate finance, Ninth Edition," *McGraw-Hill/Irwin, New York.*

Brinson, G. P., L. R. Hood, and G. L. Beebower, 1986, "Determinants of portfolio performance," *Financial Analysts Journal*, 42, 39–44.

Broadbent, D. E., 1953, "Perception and communication," *Pergamon Press, New York.*

Brown, J. R., Z. Ivkovic, P. A. Smith, and S. Weisbenner, 2008, "Neighbors matter: Causal community effects and stock market participation," *Journal of Finance*, 63, 1509–1531.

Brown, S. J., 1979, "Optimal portfolio choice under uncertainty: A bayesian approach," in *Estimation Risk and Optimal Portfolio Choice*, ed. by V. Bawa, S. Brown, and R. Klein. North Holland, Amsterdam, pp. 109–144.

Brunnermeier, M. K., and L. H. Pedersen, 2009, "Market liquidity and funding liquidity," *Review of Financial Studies*, 22, 2201–2238.

Calvet, L., J. Y. Campbell, and P. Sodini, 2007, "Down or out: Assessing the welfare costs of household investment mistakes," *Journal of Political Economy*, 115, 707–747.

Camerer, C. F., 2006, "Behavioral Economics," in *Advances in economics and econometrics: Theory and applications, Ninth World Congress*, ed. by R. Blundell, W. K. Newey, and T. Persson. Cambridge University Press, pp. 181–214.

Campbell, J. Y., 2006, "Household finance," *Journal of Finance*, 61, 1553–1604.

Carhart, M. M., 1997, "On persistence in mutual fund performance," *Journal of Finance*, 52, 57–82.

Chae, J., 2005, "Trading volume, information asymmetry, and timing information," *Journal of Finance*, 60, 413–442.

Chan, L. K., J. Lakonishok, and B. Swaminathan, 2007, "Industry classifications and return comovement," *Financial Analysts Journal*, 63, 56–70.

Chan, W. S., 2003, "Stock price reaction to news and no-news: Drift and reversal after headlines," *Journal of Financial Economics*, 70, 223–260.

Chay, J., and C. A. Trzcinka, 1999, "Managerial performance and the cross-sectional pricing of closed-end funds," *Journal of Financial Economics*, 52, 379–408.

Chemmanur, T., and A. Yan, 2009, "Advertising, attention, and stock returns," *Unpublished working paper, Boston College, Fordham University.*

Chen, H., S. Chen, and F. Li, 2010, "Empirical investigation of an equity pairs trading strategy," *Unpublished working paper, University of British Columbia, University of Michigan.*

Cherkes, M., J. Sagi, and R. Stanton, 2009, "A liquidity-based theory of closed-end funds," *Review of Financial Studies*, 22, 257–297.

Chetty, R., A. Looney, and K. Kroft, 2009, "Salience and taxation: Theory and evidence," *American Economic Review*, 99, 1145–1177.

Chopra, V. K., C. R. Hensel, and A. L. Turner, 1993, "Massaging mean variance inputs: Returns from alternative global investment strategies in the 1980s," *Management Science*, 39, 845–855.

Chordia, T., A. Goyal, and Q. Tong, 2011, "Pairwise correlations," *Unpublished working paper, Emory University, University of Lausanne, Singapore Management University.*

Chordia, T., S.-W. Huh, and A. Subrahmanyam, 2007, "The cross-section of expected trading activity," *Review of Financial Studies*, 20, 709–740.

Cohen, L., and A. Frazzini, 2008, "Economic links and predictable returns," *Journal of Finance*, 63, 1977–2011.

Cohen, L., and D. Lou, 2011, "Complicated firms," *Journal of Financial Economics, forthcoming.*

Comer, G., N. Larrymore, and J. Rodriguez, 2009, "Controlling for fixed income exposure in portfolio evaluation: Evidence from hybrid mutual funds," *Review of Financial Studies*, 22, 481–507.

Connolly, R., and C. Stivers, 2003, "Momentum and reversals in equity-index returns during periods of abnormal turnover and return dispersion," *Journal of Finance*, 58, 1521–1556.

Cooper, M. J., O. Dimitrov, and R. Rau, 2001, "A rose.com by any name," *Journal of Finance*, 56, 2371–2388.

Cooper, M. J., H. Gulen, and P. R. Rau, 2005, "Changing names with style: Mutual fund name changes and their effect on fund flows," *Journal of Finance*, 60, 2825–2858.

Corwin, S. A., and J. F. Coughenour, 2008, "Limited attention and the allocation of effort in securities trading," *Journal of Finance*, 63, 3031–3067.

Coval, J. D., and T. J. Moskowitz, 1999, "Home bias at home: Local equity preference in domestic portfolios," *Journal of Finance*, 54, 2045–2073.

———, 2001, "The geography of investment: Informed trading and asset prices," *Journal of Political Economy*, 109, 811–841.

Da, Z., J. Engelberg, and P. Gao, 2011, "In search of attention," *JF*, 66, 1461–1499.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, "Investor psychology and security market under- and overreactions," *Journal of Finance*, 53, 1839–1885.

De Roon, F. A., T. E. Nijman, and B. J. M. Werker, 2001, "Testing for mean-variance spanning with short sales constraints and transaction costs: The case of emerging markets," *Journal of Finance*, 56, 721–742.

De Santis, G., and B. Gerard, 1997, "International asset pricing and portfolio diversification with time-varying risk," *Journal of Finance*, 52, 1881–1912.

DellaVigna, S., 2009, "Psychology and economics: Evidence from the field," *Journal of Economic Literature*, 47, 315–372.

DellaVigna, S., and J. M. Pollet, 2007, "Demographics and industry returns," *American Economic Review*, 97, 1667–1702.

——— , 2009, "Investor inattention and Friday earnings announcements," *Journal of Finance*, 64, 709–749.

DeMiguel, V., L. Garlappi, F. J. Nogales, and R. Uppal, 2009a, "A generalized approach to portfolio optimization: Improving performance by constraining portfolio norms," *Management Science*, 55, 798–812.

DeMiguel, V., L. Garlappi, and R. Uppal, 2009b, "Optimal versus naive diversification: How efficient is the 1/N portfolio strategy?," *Review of Financial Studies*, pp. 1915–1953.

Do, B., and R. Faff, 2010, "Does simple pairs trading still work?," *Financial Analysts Journal*, 66, 83–95.

Do, B. H., and R. W. Faff, 2011, "Are pairs trading profits robust to trading costs?," *Journal of Financial Research, forthcoming*.

Dorn, D., and G. Huberman, 2005, "Talk and action: What individual investors say and what they do," *Review of Finance*, 9, 437–481.

Dorn, D., G. Huberman, and P. Sengmueller, 2008, "Correlated trading and returns," *Journal of Finance*, 63, 885–920.

Driessen, J., and L. Laeven, 2007, "International portfolio diversification benefits: Cross-country evidence from a local perspective," *Journal of Banking and Finance*, 31, 1693–1712.

Duchin, R., and H. Levy, 2009, "Markowitz versus the talmudic portfolio diversification strategies," *Journal of Portfolio Management*, 35, 71–74.

Engelberg, J., 2008, "Costly information processing: Evidence from earnings announcements," *Unpublished working paper, Northwestern University.*

Engelberg, J., P. Gao, and R. Jagannathan, 2009, "An anatomy of pairs trading: The role of idiosyncratic news, common information and liquidity," *Unpublished working paper, University of North Carolina, University of Notre Dame, Northwestern University.*

Engelberg, J., C. Sasseville, and J. Williams, 2011, "Market madness? The case of mad money," *Management Science, forthcoming.*

Ennis, R. M., and M. D. Sebastian, 2005, "Asset allocation with private equity," *Journal of Private Equity*, 8, 81–87.

Erb, C. B., and C. R. Harvey, 2006, "The strategic and tactical value of commodity futures," *Financial Analysts Journal*, 62, 69–97.

Eun, C. S., W. Huang, and S. Lai, 2008, "International diversification with large- and small-cap stocks," *Journal of Financial and Quantitative Analysis*, 43, 489–524.

Eun, C. S., and B. G. Resnick, 1994, "International diversification of investment portfolios: U.S. and Japanese perspectives," *Management Science*, 40, 140–161.

Fama, E., and K. R. French, 2010, "Luck versus skill in the cross section of mutual fund returns," *Journal of Finance*, 65, 1915–1947.

Fama, E. F., 1970, "Efficient capital markets: A review of theory and empirical evidence," *Journal of Finance*, 25, 383–417.

——— , 1998, "Market efficiency, long-term returns, and behavioral finance," *Journal of Financial Economics*, 49, 283–306.

Fama, E. F., and K. R. French, 1993, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

——— , 1997, "Industry costs of equity," *Journal of Financial Economics*, 43, 153–193.

Fang, L., and J. Peress, 2009, "Media coverage and the cross-section of stock returns," *Journal of Finance*, 64, 2023–2052.

Farinelli, S., M. Ferreira, D. Rossello, M. Thoeny, and L. Tibiletti, 2008, "Beyond Sharpe ratio: Optimal asset allocation using different performance ratios," *Journal of Banking and Finance*, 32, 2057–2063.

——— , 2009, "Optimal asset allocation aid system: From one-size vs. tailor-made performance ratio," *European Journal of Operational Research*, 192, 209–215.

Feng, L., and M. S. Seasholes, 2004, "Correlated trading and location," *Journal of Finance*, 59, 2117–2144.

Fink, J., K. E. Fink, G. Grullon, and J. P. Weston, 2010, "What drove the increase in idiosyncratic volatility during the internet boom?," *Journal of Financial and Quantitative Analysis*, 45, 1253–1278.

Frankfurter, G. M., H. E. Phillips, and J. P. Seagle, 1971, "Portfolio selection: The effects of uncertain means, variances and covariances," *Journal of Financial and Quantitative Analysis*, 6, 1251–1262.

French, K. R., and J. M. Poterba, 1991, "Investor diversification and international equity markets," *American Economic Review*, 81, 222–226.

Frieder, L., and A. Subrahmanyam, 2004, "Non-secular regularities in returns and volume," *Financial Analysts Journal*, 60, 29–34.

Froot, K. A., and E. M. Dabora, 1999, "How are stock prices affected by the location of trade?," *Journal of Financial Economics*, 53, 189–216.

Gagnon, L., and G. A. Karolyi, 2010, "Multi-market trading and arbitrage," *Journal of Financial Economics*, 97, 53–80.

Gao, X., and T.-C. Lin, 2010, "Do behavioral needs influence the trading activity of individual investors? Evidence from repeated natural experiments," *Unpublished working paper, University of Hong Kong.*

Gatev, E. G., W. N. Goetzmann, and K. G. Rouwenhorst, 2006, "Pairs trading: Performance of a relative-value arbitrage rule," *Review of Financial Studies*, 19, 797–827.

Gilbert, T., S. Kogan, L. Lochstoer, and A. Ozyildirim, 2011, "Investor inattention and the market impact of summary statistics," *Unpublished working paper, University of Washington, University of Texas at Austin, Columbia University, The Conference Board.*

Glaser, M., and M. Weber, 2007, "Overconfidence and trading volume," *Geneva Risk and Insurance Review*, 32, 1–36.

———, 2009, "Which past returns affect trading volume?," *Journal of Financial Markets*, 12, 1–31.

Goetzmann, W. N., and A. Kumar, 2008, "Equity portfolio diversification," *Review of Finance*, 12, 433–463.

Goetzmann, W. N., L. Li, and K. G. Rouwenhorst, 2005, "Long-term global market correlations," *Journal of Business*, 78, 1–38.

Gorton, G., and K. G. Rouwenhorst, 2006, "Facts and fantasies about commodity futures," *Financial Analysts Journal*, 62, 47–62.

Green, T. C., and B.-H. Hwang, 2009, "Price-based return comovement," *Journal of Financial Economics*, 93, 37–50.

Greenwood, R., 2008, "Excess comovement of stock returns: Evidence from cross-sectional variation in Nikkei 225 weights," *Review of Financial Studies*, 21, 1153–1186.

Griffin, J. M., 2002, "Are the Fama and French factors global or country specific?," *Review of Financial Studies*, 15, 783–803.

Grinblatt, M., and M. Keloharju, 2001, "How distance, language, and culture influence stockholdings and trades," *Journal of Finance*, 56, 1053–1073.

Gromb, D., and D. Vayanos, 2002, "Equilibrium and welfare in markets with financially constrained arbitrageurs," *Journal of Financial Economics*, 66, 361–407.

———, 2010, "Limits of arbitrage: The state of the theory," *Annual Review of Financial Economics*, 2, 251–275.

Grossman, S. J., and J. E. Stiglitz, 1980, "On the impossibility of informationally efficient markets," *American Economic Review*, 70, 393–408.

Grullon, G., G. Kanatas, and J. P. Weston, 2004, "Advertising, breadth of ownership, and liquidity," *Review of Financial Studies*, 17, 439–461.

Hau, H., 2001, "Location matters: An examination of trading profits," *Journal of Finance*, 56, 1959–1983.

Haugen, R. A., and N. L. Baker, 1991, "The efficient market inefficiency of capitalization-weighted stock portfolios," *Journal of Portfolio Management*, 17, 35–40.

Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang, 2004, "Do investors overvalue firms with bloated balance sheets?," *Journal of Accounting and Economics*, 38, 297–331.

Hirshleifer, D., S. S. Lim, and S. H. Teoh, 2009, "Driven to distraction: Extraneous events and underreaction to earnings news," *Journal of Finance*, 64, 2289–2325.

Hirshleifer, D., and S. H. Teoh, 2003, "Limited attention, information disclosure, and financial reporting," *Journal of Accounting and Economics*, 36, 337–386.

Hong, H. G., J. D. Kubik, and T. Fishman, 2011, "Do arbitrageurs amplify economic shocks?," *Journal of Financial Economics, forthcoming.*

Hong, H. G., J. D. Kubik, and J. C. Stein, 2004, "Social interaction and stock-market participation," *Journal of Finance*, 59, 137–163.

——— , 2005, "Thy neighbor's portfolio: Word-of-mouth-effects in the holdings and trades of money managers," *Journal of Finance*, 60, 2801–2824.

——— , 2008, "The only game in town: Stock-price consequences of local bias," *Journal of Financial Economics*, 90, 20–37.

Hong, H. G., T. Lim, and J. C. Stein, 2000, "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies," *Journal of Finance*, 55, 265–295.

Hong, H. G., and J. C. Stein, 1999, "A unified theory of underreaction, momentum trading, and overreaction in asset markets," .

——— , 2007, "Disagreement and the stock market," *Journal of Political Economy*, 36, 3–27.

Hong, H. G., W. Torous, and R. Valkanov, 2007, "Do industries lead stock markets?," *Journal of Financial Economics*, 83, 367–396.

Hong, H. G., and J. Yu, 2009, "Gone fishin': Seasonality in trading activity and asset prices," *Journal of Financial Markets*, 12, 672–702.

Hossain, T., and J. Morgan, 2006, "...plus shipping and handling: revenue (non)equivalence in field experiments on eBay," *B.E. Journals in Economic Analysis and Policy: Advances in Economic Analysis and Policy*, 6, 1–27.

Hou, K., 2007, "Industry information diffusion and the lead-lag effect in stock returns," *Review of Financial Studies*, 20, 1113–1138.

Hou, K., and T. Moskowitz, 2005, "Market frictions, price delay, and the cross-section of expected returns," *Review of Financial Studies*, 18, 981–1020.

Hou, K., L. Peng, and W. Xiong, 2009, "A tale of two anomalies: The implications of investor attention for price and earnings momentum," *Unpublished working paper, Ohio State University, City University of New York, Princeton University.*

Huang, L., and H. Liu, 2007, "Rational inattention and portfolio selection," *Journal of Finance*, 62, 1999–2040.

Huberman, G., 2001, "Familiarity breeds investment," *Review of Financial Studies*, 14, 659–680.

Huberman, G., and T. Regev, 2001, "Contagious speculation and a cure for cancer: A non-event that made stock prices soar," *Journal of Finance*, 56, 387–396.

Ibbotson, R. G., and P. D. Kaplan, 2000, "Does asset allocation policy explain 40, 90 or 100 percent of performance?," *Financial Analysts Journal*, 56, 26–33.

Ince, O. S., and R. B. Porter, 2006, "Individual equity return data from Thomson Datastream: Handle with care!," *Journal of Financial Research*, 29, 463–479.

Ivkovic, Z., and S. Weisbenner, 2005, "Local does as local is: Information content of the geography of individual investors' common stock investments," *Journal of Finance*, 60, 267–306.

——— , 2007, "Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices," *Review of Financial Studies*, 20, 1327–1357.

Jagannathan, R., and T. Ma, 2003, "Risk reduction in large portfolios: Why imposing the wrong constraints helps," *Journal of Finance*, 58, 1651–1683.

James, W., and C. Stein, 1961, "Estimation with quadratic loss," *Procedings of the Fourth Berkeley Symposium on Probability and Statistics*, 1, 361–380.

Jensen, M. C., 1968, "The performance of mutual funds in the period 1945 - 1964," *Journal of Finance*, 23, 389 – 416.

Jobson, J. D., and B. M. Korkie, 1981, "Performance hypothesis testing with the Sharpe and Treynor measures," *Journal of Finance*, 36, 889–908.

Jong, A. D., L. Rosenthal, and M. A. V. Dijk, 2009, "The risk and return of arbitrage in dual-listed companies," *Review of Finance*, 13, 495–520.

Jorion, P., 1985, "International portfolio diversification with estimation risk," *Journal of Business*, 58, 259–278.

Kacperczyk, M., S. V. Nieuwerburgh, and L. Veldkamp, 2011, "Rational attention allocation over the business cycle," *Unpublished Working Paper, New York University.*

Kahneman, D., 1973, *Attention and effort.* Prentice Hall, New Jersey.

——— , 2003, "Maps of bounded rationality: Psychology for behavioral economics," *American Economic Review*, 93, 1449–1475.

Karlsson, N., G. Loewenstein, and D. Seppi, 2009, "The ostrich effect: Selective attention to information," *Journal of Risk and Uncertainty*, 38, 95–115.

Kilka, M., and M. Weber, 2000, "Home bias in international stock return expectations," *Journal of Psychology and Financial Markets*, 1, 176–192.

Kimball, M. S., and T. Shumway, 2010, "Investor sophistication and the home bias, diversification, and employer stock puzzles," Unpublished working paper, University of Michigan.

Klibanoff, P., O. Lamont, and T. A. Wizman, 1998, "Investor reaction to salient news in closed-end country funds," *Journal of Finance*, 53, 673–699.

Korniotis, G. M., and A. Kumar, 2010, "State-level business cycles and local return predictability," *Unpublished working paper, University of Miami.*

Kritzman, M., S. Page, and D. Turkington, 2010, "In defense of optimization: The fallacy of 1/N," *Financial Analysts Journal*, 66, 31–39.

Kumar, A., and C. C. Lee, 2006, "Retail investor sentiment and return comovements," *Journal of Finance*, 61, 2451–2486.

Lamont, O. A., and R. H. Thaler, 2003a, "Can the market add and subtract? Mispricing in tech stock carve-outs," *Journal of Political Economy*, 111, 227–268.

——— , 2003b, "The law of one price in financial markets," *Journal of Economic Perspectives*, 17, 191–202.

Ledoit, O., and M. Wolf, 2004, "Honey, I shrunk the sample covariance matrix," *Journal of Portfolio Management*, 31, 110–119.

——— , 2008, "Robust performance hypothesis testing with the Sharpe ratio," *Journal of Empirical Finance*, 15, 850–859.

Lee, C. M., A. Shleifer, and R. H. Thaler, 1991, "Investor sentiment and the closed-end fund puzzle," *Journal of Finance*, 46, 75–109.

Libby, R., R. Bloomfield, and M. W. Nelson, 2002, "Experimental research in financial accounting," *Accounting, Organizations and Society*, 27, 775–810.

Lo, A. W., and C. A. MacKinlay, 1990, "When are contrarian profits due to stock market overreaction?," *Review of Financial Studies*, 3, 175–205.

Lo, A. W., and J. Wang, 2000, "Trading volume: Definitions, data analysis, and implications of portfolio theory," *Review of Financial Studies*, 13, 257–300.

Loh, R., 2010, "Investor inattention and the underreaction to stock recommendation," *Financial Management*, 39, 1223–1251.

Long, J. B. D., A. Shleifer, L. H. Summers, and R. J. Waldmann, 1990, "Noise trader risk in financial markets," *Journal of Political Economy*, 98, 703–738.

Longin, F., and B. Solnik, 2001, "Extreme correlation of international equity markets," *Journal of Finance*, 56, 649–676.

Lou, D., 2010, "Maximizing short-term stock prices through advertising," *Unpublished working paper, London School of Economics.*

Loughran, T., and P. Schultz, 2004, "Weather, stock returns, and the impact of localized trading behavior," *Journal of Financial and Quantitative Analysis*, 39, 343–364.

——— , 2005, “Liquidity: Urban versus rural firms,” *Journal of Financial Economics*, 78, 341–374.

Louis, H., and A. Sun, 2010, “Investor inattention and the market reaction to merger announcements,” *Management Science*, 56, 1781–1793.

Lyon, J. D., B. M. Barber, and C.-L. Tsai, 1999, “Improved methods for tests of long-run abnormal stock returns,” *Journal of Finance*, 54, 165–201.

Markowitz, H., 1952, “Portfolio selection,” *Journal of Finance*, 7, 77–91.

Massa, M., and A. Simonov, 2006, “Hedging, familiarity and portfolio choice,” *Review of Financial Studies*, 19, 633–685.

Menzly, L., and O. Ozbas, 2010, “Market segmentation and cross-predictability of returns,” *Journal of Finance*, 65, 1555–1580.

Merton, R. C., 1987, “A simple model of capital market equilibrium with incomplete information,” *Journal of Finance*, 42, 483–510.

Michaud, R. O., 1998, *Efficient asset management: A practical guide to stock portfolio optimization and asset allocation.* Oxford University Press, New York.

Mitchell, M., T. Pulvino, and E. Stafford, 2002, “Limited arbitrage in equity markets,” *Journal of Finance*, 57, 551–584.

Modigliani, F., and L. Modigliani, 1997, “Risk-adjusted performance,” *Journal of Portfolio Management*, 23, 45–54.

Mullainathan, S., and R. Thaler, 2001, “Behavioral Economics,” in *International Encyclopedia of the Social and Behavioral Sciences*, ed. by N. Smelser, and P. Bates. Elsevier, Oxford, pp. 1094–1100.

Nagel, S., 2011, “Evaporating Liquidity,” *Unpublished working paper, Stanford University.*

Odean, T., 1998, “Are investors reluctant to realize their losses?,” *Journal of Finance*, 53, 1775–1798.

——— , 1999, “Do investors trade too much?,” *American Economic Review*, 89, 1279–1298.

Pashler, H. E., 1998, *The psychology of attention.* MIT Press, Cambridge.

Pástor, L., and R. F. Stambaugh, 2003, "Liquidity risk and expected stock returns," *Journal of Political Economy*, 111, 642–685.

Patton, A. J., 2009, "Are "market neutral" hedge funds really market neutral?," *Review of Financial Studies*, 22, 2495–2530.

Peng, L., 2005, "Learning with information capacity constraints," *Journal of Financial and Quantitative Analysis*, 40, 307–329.

Peng, L., and W. Xiong, 2006, "Investor attention, overconfidence and category learning," *Journal of Financial Economics*, 80, 563–602.

Peng, L., W. Xiong, and T. Bollerslev, 2007, "Investor attention and time-varying comovements," *European Financial Management*, 13, 394–422.

Peress, J., 2008, "Media coverage and investors' attention to earnings announcements," *Unpublished working paper, Insead.*

Petersen, M. A., 2009, "Estimating standard errors in finance panel data sets: Comparing approaches," *Review of Financial Studies*, 22, 435–480.

Petrella, G., 2005, "Are euro area small cap stocks an asset class? Evidence from mean-variance spanning tests," *European Financial Management*, 11, 229–253.

Phalippou, L., and O. Gottschalg, 2009, "The performance of private equity funds," *Review of Financial Studies*, 22, 1747–1776.

Pirinsky, C., and Q. Wang, 2006, "Does corporate headquarters location matter for stock returns?," *Journal of Finance*, 61, 1991–2015.

Polkovnichenko, V., 2005, "Household portfolio diversification: A case for rank dependent preferences," *Review of Financial Studies*, 18, 1467–1502.

Pontiff, J., 1995, "Closed-end fund premia and returns implications for financial market equilibrium," *Journal of Financial Economics*, 37, 341–370.

———, 2006, "Costly arbitrage and the myth of idiosyncratic risk," *Journal of Accounting and Economics*, 42, 35–52.

Rachev, S. T., T. Jaic, S. Stoyanov, and F. J. Fabozzi, 2007, "Momentum strategies based on reward-risk stock selection criteria," *Journal of Banking and Finance*, 31, 2325–2346.

Rosenthal, L., and C. Young, 1990, "The seemingly anomalous price behavior of Royal Dutch/Shell and Unilever N.V./PLC," *Journal of Financial Economics*, 26, 123–141.

Schultz, P., and S. Shive, 2010, "Mispricing of dual-class shares: Profit opportunities, arbitrage, and trading," *Journal of Financial Economics*, 98, 524–549.

Scruggs, J. T., 2007, "Noise trader risk: Evidence from the Siamese twins," *Journal of Financial Markets*, 10, 76–105.

Seasholes, M. S., and G. Wu, 2007, "Predictable behavior, profits, and attention," *Journal of Empirical Finance*, 14, 590–610.

Seasholes, M. S., and N. Zhu, 2010, "Individual investors and local bias," *Journal of Finance*, 65, 1987–2011.

Shefrin, H., and M. Statman, 1985, "The disposition to sell winners too early and ride losers too long: Theory and evidence," *Journal of Finance*, 40, 777–790.

Shiller, R. J., 1981, "Do stock prices move too much to be justified by subsequent changes in dividends?," *American Economic Review*, 71, 421–436.

Shive, S., 2010, "An epidemic model of investor behavior," *Journal of Quantitative and Financial Analysis*, 45, 169–198.

Shive, S. A., 2011, "Local investors, price discovery and market efficiency," *Journal of Financial Economics, forthcoming.*

Shleifer, A., 2000, "Inefficient markets: An introduction to behavioral finance," *Oxford University Press, New York.*

Shleifer, A., and L. Summers, 1990, "The noise trader approach to finance," *Journal of Economic Perspectives*, 4, 19–33.

Shleifer, A., and R. W. Vishny, 1997, "The limits of arbitrage," *Journal of Finance*, 52, 35–55.

Siegel, J. J., 2006, "The 'noisy market' hypothesis," *The Wall Street Journal*, June 14 2006.

Smith, B. F., and B. Amoako-Adu, 1995, "Relative prices of dual class shares," *Journal of Financial and Quantitative Analysis*, 30, 223–239.

Statman, M., S. Thorley, and K. Vorkink, 2006, "Investor overconfidence and trading volume," *Review of Financial Studies*, 19, 1531–1565.

Stivers, C., and L. Sun, 2010, "Cross-sectional return dispersion and time variation in value and momentum premiums," *Journal of Financial and Quantitative Analysis*, 45, 987–1014.

Tang, N., O. S. Mitchell, G. R. Mottola, and S. P. Utkus, 2010, "The efficiency of sponsor and participant portfolio choices in 401(K) plans," *Journal of Public Economics*, 94, 1073–1085.

Tetlock, P. C., 2010, "Does public financial news resolve asymmetric information?," *Review of Financial Studies*, 23, 3520–3557.

———, 2011, "All the news that's fit to reprint: Do investors react to stale information?," *Review of Financial Studies*, 24, 1481–1512.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy, 2008, "More than words: Quantifying language to measure firms' fundamentals," *Journal of Finance*, 63, 1437–1467.

Tkac, P. A., 1999, "A trading volume benchmark: Theory and evidence," *Journal of Financial and Quantitative Analysis*, 34, 89–114.

Treynor, J., 2005, "Why market-valuation-indifferent indexing works," *Financial Analysts Journal*, 61, 65–69.

Tu, J., and G. Zhou, 2011, "Markowitz meets Talmud: A combination of sophisticated and naive diversification strategies," *Journal of Financial Economics*, 99, 204–215.

Weber, M., and C. F. Camerer, 1998, "The disposition effect in securities trading: An experimental analysis," *Journal of Economic Behavior & Organization*, 33, 167–184.

West, K. D., and W. K. Newey, 1987, "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703–708.

Womack, K. L., 1996, "Do brokerage analysts' recommendations have investment value?," *Journal of Finance*, 51, 137–167.

Yuan, Y., 2009, "Attention and trading," *Unpublished working paper, University of Iowa.*

Zhu, N., 2003, "The local bias of individual investors," *Unpublished working paper, Yale University.*

Zingales, L., 1995, "What determines the value of corporate votes?," *Quarterly Journal of Economics*, 110, 1047–1073.

Heiko Jacobs

Schulausbildung und akademischer Werdegang:

Juni 2001	Abitur, Ludwigsgymnasium, Saarbrücken
August 2001 bis Juni 2002	Zivildienst, Landesamt für Umweltschutz, Saarbrücken
Oktober 2002 bis December 2006	Studium der Betriebswirtschaftslehre, Universität des Saarlandes, Abschluss als Diplom-Kaufmann
Februar 2007 bis August 2007	Auslandsaufenthalt an der University of Technology, Sydney
Seit September 2007	Wissenschaftlicher Mitarbeiter am Lehrstuhl für ABWL, Finanzwirtschaft, insb. Bankbetriebslehre der Universität Mannheim
28. November 2011	Promotion an der Universität Mannheim Prüfung zum Dr. rer. pol. mit "summa cum laude"