Università della Svizzera Italiana

Doctoral Thesis

Frictions, Behavioral Biases and Active Portfolio Management

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Abstract

The three chapters of this thesis contribute to the following research questions: (i) What is the role of agency frictions for the performance of mutual funds? (ii) What is the role of market frictions for the performance of hedge funds? (iii) Do hedge funds profit from the behavioral biases of other market participants?

The first chapter of this thesis comprises the article "Are Star Funds really Shining? Cross-trading and Performance Shifting in Mutual Fund Families", which is joint work with my colleagues Tamara Nefedova and Gianpaolo Parise. This article exploits institutional trade level data to study cross-trading activity inside mutual fund families. Cross-trades are opposite trades matched between siblings (i.e., funds belonging to the same fund family) without going to the open market. We find that large fund families with weak governance and high within family size dispersion cross-trade more and are more likely to misprice their cross-trades. Additionally, we find that cross-trades are used to increase the performance of the most valuable siblings (on average by 2.5% per annum) at the expense of the less valuable funds. More restrictive governance policies introduced as a consequence of the late trading scandal were effective in reducing the amount and the mispricing of cross-trades.

The second chapter comprises the solo-authored article "Beta Arbitrage and Hedge Fund Returns". This article finds that a factor capturing the returns of strategies exploiting the low beta anomaly, i.e. a betting-against-beta factor (BAB), has significant explanatory power in the time-series and cross-section of hedge fund returns. Controlling for the exposure towards this factor drives risk-adjusted returns (alpha) of most hedge fund style returns to zero. In line with theory, the cross-sectional dispersion in the factor exposure is driven by the access to leverage and the contractual relationship between hedge fund managers and investors. Finally, hedge funds with a high loading on the BAB factor outperform funds with a low loading by 0.88% monthly on a risk-adjusted basis in the period from 1999-2008.

The third chapter comprises the solo-authored article " Behavioral Factors in Risk Arbitrage". In the context of takeovers, the article examines the trading behavior of investors around a salient reference point, the 52-week high, and its effect on asset prices. Using a large sample of institutional trade-level data the article documents a 50% increase in institutional investor exit at the announcement date for offer prices exceeding the 52-week high. The increased selling pressure leads to significant stock price underreaction and explains a large part of the returns in risk arbitrage. A risk arbitrage strategy exploiting the underreaction generates annual alphas of up to 11.9% with a sharpe ratio of 1.63 in the US and in a large sample of over 7000 international takeover transactions. Consistent with limits to arbitrage, the trading strategy's profits vary negatively with the available capital in the arbitrage sector. I rule out several alternative explanations for my results and finally, using trading costs estimated from institutional trade-level data and a parametric portfolio policy approach, the paper demonstrates the economic significance of the effect controlling for other behavioral and rational return predictors in risk arbitrage.

Keywords: Hedge Funds, Mutual Funds, Behavioral Finance, Risk Arbitrage, Portfolio Management, Low-Beta Anomaly

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Working in a team is often more enjoyable than working alone. When deadlines approached our working relationship was not always smooth, but overall Tamara Nefedova, Gianpaolo Parise and me had a lot of fun with our joint project and became good friends. I thank them for working with me and for countering my chronic pessimism with their fierce optimism. I would not want to miss the countless discussions surrounding our research project and our future.

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Dedicated to my Family

Chapter 1

Are Star Funds Really Shining? Cross-Trading and Performance Shifting in Mutual Fund Families

(joint with Tamara Nefedova and Gianpaolo Parise)

1.1 Introduction

Delegated portfolio management creates a principal-agent problem because the fund investor (principal) can only imperfectly monitor the fund manager (agent), and their incentives are not necessarily aligned[1]. This conflict of interest can be magnified when a fund is not a standalone entity, but belongs to a mutual fund family. In particular, affiliation with a mutual fund family implies that a portfolio manager is first of all working for the family and not for the fund's investors.

In this paper we study how the tension between fund interests, family interests and shareholder interests impacts a fund family's performance distribution. Specifically, using a unique institutional trade-level dataset we examine the cross-trading activity inside mutual fund families and its consequence on performance. Cross-trades are transactions where buy and sell orders for the same stock coming from the same fund family are offset by the broker without going into the open market. Cross-trades are permitted under rule 17a-7 of the U.S. Investment Company Act and can be beneficial for mutual fund investors since they reduce trading costs and commissions. However, unfairly

[1]There is a significant literature suggesting that money manager opportunistically try to present a "rosier" version of reality to their investors, see, e.g., Lakonishok et al. [1], Sias and Starks [2], Ben-David et al. [3] on window dressing practices.

priced cross-trades are illegal and potentially shift performance between the two parties involved in the trade.

Previous literature has provided evidence of illegal performance shifting consistent with cross-trading. However, due to data availability previous papers infer potential cross-trading activity from quarterly holdings data[2] (see e.g. Gaspar et al. [4], Goncalves-Pinto and Sotes-Paladino [5]) or indirectly from return level data (see Chaudhuri et al. [6]) with controversial findings. In contrast, from our institutional trade-level dataset provided by Ancerno we identify cross-trades as trades executed within the same fund family, in the same stock, with the same volume, the same execution price, the same execution date and the same execution time but in opposite trade directions. Thus, we provide a significantly more precise proxy for cross-trading activity. Additionally, having the cross trades' execution prices we can directly assess any impact on performance.

We begin our empirical analysis studying the determinants of cross-trading activity and find supporting evidence for the hypothesis that cross-trading is used to shift performance across different funds. First, cross-trading activity is significantly higher in fund families with weak governance. Second, in line with the argument that a large difference in product sizes would allow to move performance from big to small products at low cost (Chaudhuri et al. [6]) we find that cross-trading activity increases when there are large size differences between funds in the family. Third, consistent with the incentive of creating "star funds" stressed in Nanda et al. [7] cross-trading activity is increasing in the intra-family dispersion of returns. Besides testing the cross-sectional determinants of cross-trading activity we also study the time-series determinants. At the beginning of 2004, the U.S. Securities and Exchange Commission (SEC) made several amendments to industry regulations, as a response to the "late trading scandal". Among the new requirements, fund families were asked to employ a compliance officer and to enforce compliance policies. We hypothesize that the presence of a compliance officer dampened any unlawful behavior inside fund families. Hence, if cross-trading was primarily used

[2]Using quarterly holdings it is not possible to distinguish whether two funds trading the same stock in opposite directions are trading during the same day or in different months. Hence, the resulting proxies of cross-trading activity are upward biased.

to illegally shift performance across funds, it should decrease after 2004. Our results suggest that indeed cross-trading activity decreased significantly after 2004.

Families are only able to shift performance via cross-trades when the execution prices of the trades deviate significantly from the market price at the time of order execution. In the next step we therefore compare execution prices of cross-trades to the volume weighted average execution price of the day (VWAP). We find that cross-trades in our sample are often mispriced, displaying execution prices up to 2% away from VWAP. Furthermore, the families that cross-trade the most are also more likely to cross-trade at prices far away from the VWAP. Finally, the requirement to employ a compliance officer pushed the execution prices of cross-trades significantly towards the VWAP implying a lesser degree of performance redistribution across funds.

Our aforementioned results are suggestive of performance shifting at the mutual fund family level. However, our findings about the mispricing of cross-trades are consistent with two different strategies. First, in line with Goncalves-Pinto and Sotes-Paladino [5], Bhattacharya et al. [8], Schmidt and Goncalves-Pinto [9] families can shift performance via cross-trades in order to smooth performance across different funds in the family. Such a strategy would help low value funds that suffer because of investor redemptions at the expense of high value siblings[3]. We refer to such a strategy as performance smoothing. Second, in line with the incentive of fund families to enhance the performance of the most valuable funds (see Guedj and Papastaikoudi [10], Gaspar et al. [4], and Evans [11]) fund families can use cross-trades to play favorites, increasing the performance of high value funds while hurting the performance of the less valuable funds.

To distinguish between the two different strategies we study mutual fund returns employing an empirical strategy motivated by the seminal paper of Gaspar et al. [4]. In particular, we study the differences in risk-adjusted returns between funds having a high value for the fund family and funds having a low value for the fund family and test whether the amount of cross-trading activity has a significant impact on this difference. Following the literature (see, e.g., Bhattacharya et al. [8]) we define high-value funds as

[3] We refer to "high value" ("low value") siblings to indicate funds that we conjecture to be particularly important (unimportant) for the family, e.g., because they are able to attract high (low) flows or charge high (low) fees.

funds with flows in the top tercile of the fund family flow distribution and low value funds as funds with flows in the bottom tercile. We regress their spread in performance on the percentage of cross-trading within their family conditional of being in the same investment style and controlling for differences in fund size, past performance and past flows plus other family level controls. We find that an increase by one standard deviation in within family cross-trading increases the gap in the alphas between high value and low value funds by 22 basis points per month (51 bps if we consider the spread in raw returns). Additionally, we use mutual fund fees as a sorting variable instead of flows (consistent with Gaspar et al. [4]) and find similar results. Finally, we replace the level of cross-trading with the monthly average mispricing of cross-trades in the family as our independent variable of interest and obtain results in line with our previous tests.

Our analysis is motivated by a recent legal action of the Security and Exchange Commission against Western Asset Management. The investment firm allegedly executed the sell side of cross transactions at the highest current independent bid price available for the securities. By cross trading securities at the bid, rather than at an average between the bid and the ask, Western favored the buyers in the transactions over the sellers, even though both were advisory clients of Western and owed the same fiduciary duty. As a result, Western deprived its selling clients of approximately $6.2 million. According to the SEC Western's cross-trading violations were caused in large part by its failure to adopt adequate policies and procedures to prevent unlawful cross-trading[4].

Hence, to make sure our results are really driven by opportunistic practices, we explore how time-series and cross-sectional differences in family governance affect our results. We find performance shifting to be almost 10 times less effective after 2003 when the new SEC regulation was implemented. Furthermore, performance shifting via cross-trades is significantly stronger in fund families with weak family governance.

Overall, our results indicate that fund families exploit cross-trades to improve the performance of high value funds at the expense of low value siblings. This finding is consistent with the incentive of mutual fund families to improve the performance of their best funds in order to attract new inflows. According to Chevalier and Ellison [12], the shape of the

[4]See administrative proceeding No. 3-15688 of January 27, 2014. Similar evidence is provided by the SEC case against BNY Mellon, administrative proceeding No. 3-14191 of January 14, 2011.

flow-performance relationship serves as an implicit incentive contract for mutual funds. Mutual funds earn their fees based on their assets under management and this creates incentives for them to attract new assets to manage. In the same vein mutual fund complexes desire to attract flows to the family to collect more fees. Increasing returns of a high value sibling at the expense of a less expensive fund is optimal if we take into account the findings of Sirri and Tufano [13] showing that an improvement in the returns of a good fund disproportionally attracts new inflows, while on the contrary, the outflows of the worst performing funds are less affected by a further drop in performance.

The incentive for fund families to play favorite is stressed in Gaspar et al. [4]. The authors empirically document that favorite funds (e.g., high-fee funds) outperform less valuable funds. While Nanda et al. [7] show empirically that one fund in the family outperforming the rest of the market has a significant positive impact in terms of fund flows on all other funds in the family. Thus, strategically shifting performance to create one "star" fund in the family can be rational from family perspective despite simultaneously decreasing the returns for some fund investors.

This paper makes two contributions to the literature. First, a large debate in this field concerns whether siblings help or exploit funds in the same families that suffer because of money redemptions. Cross-trading is probably the easiest way for equity funds to shift performance from or to other siblings. However, mutual funds are required to publish their holdings at a quarterly frequency. Hence, previous literature was forced to estimate imprecise proxies of cross-trading activity out of low-frequency data. As a consequence, other papers find controversial results. In this paper we exploit high-frequency transaction data to build a reliable proxy of cross-trading activity. Our finding supports the hypothesis that performance is shifted from low value funds to the most valuable siblings in the family despite fiduciary duties would demand to treat all funds equally.

Second, we show that cross-trading has an enormous impact on the ability of funds to generate "alpha". We find that cross-trading boosts the risk-adjusted performance of top funds of roughly 1.0% per year on average (causing an equivalent loss for the least important funds) compared to funds belonging to families that display no cross-trading activity. Furthermore, this artificially constructed performance is "pure alpha" because it is uncorrelated to any risky factors. The mutual fund literature (as well as mutual fund clients) heavily relies on past alpha as a proxy of a fund manager's skill. However, our results suggest that a large fraction of alpha has nothing to do with skill but is simply an effect of performance redistribution. Consistently, the decreased cross-trading activity following the late trading scandal may contribute to explain the decreased "ability" of fund managers to generate risk-adjusted performance observed in the last decade (see, e.g., Pastor et al. [14]).

This paper proceeds as follows. Section 2 describes the data we used. In Section 3 we document cross-trading activity. Section 4 disentangles between the cooperation and the favoritism hypotheses. Section 5 presents additional robustness checks. Section 6 concludes.

1.2 Data

For our analysis we compile data from four different sources. First, we use the CRSP Survivor Bias Free US Mutual Fund Database to obtain mutual fund returns and characteristics. Second, we use the MFLinks table provided by WRDS. Third, we use a table provided by WRDS linking management companies from SEC 13F filings to mutual funds reporting their holdings in the Thomson Reuter's S12 holdings database. Finally, we use institutional trade-level data provided by Abel Noser Solutions/ANcerno, a consulting firm that works with institutional investors to monitor their trading costs.

1.2.1 Mutual Fund Data

Our dataset construction starts with a merge between the CRSP database, the MFLinks table and information concerning the management companies. The merge with the MFLinks table allows us to aggregate mutual fund information across different share classes and deletes all funds not trading in equities. Furthermore, it provides an identifier to match management companies to the mutual funds. After the merging of the datasets we impose two filters. As the focus of our analysis is on mutual fund families we exclude families with less than three family members. The requirement to have at least three funds trading in equities is driven by our empirical methodology and is explained later. Additionally, we impose a minimum number of return observations for a fund to be included in our sample. In our empirical analysis our dependent variables are raw returns as well as risk-adjusted returns. For the risk adjustment we have to run time-series regressions at the fund level to compute Carhart [15] four factor alphas. To ensure reliable estimates we require a fund to have at least a 3-year return history. Finally, we focus on data between 1999 and 2010 where the ANcerno data is available to us.

Besides mutual fund alphas, we obtain several other variables important for our analysis from the CRSP Mutual Fund Database and the Thomson holdings data. On the fund level we obtain a mutual fund's size, its fees and its flows. Following Gaspar et al. [4] we compute fees as 1/7(frontload+rearload)+expense ratio. For the flows we follow the literature (e.g. Coval and Stafford [16]) and compute them as

$$FLOW_{it} = \frac{TNA_{it} - (1 + ret_{it})TNA_{it-1}}{TNA_{it-1}},$$

where TNA are the total net assets under management and ret is the monthly return of fund i in month t. On the family level we obtain the family size, the intra-family return dispersion and the intra-family size dispersion. Family size is the defined as the sum of the individual funds' assets. For intra-family return dispersion we follow Nanda et al. [7] and compute it as

$$ReturnDispersion_{ft} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\alpha_{it} - \bar{\alpha}_{ft})},$$

where α_{it} is the four-factor alpha of fund i in month t and $\bar{\alpha}_{ft}$ is the mean of four-factor adjusted returns of all siblings within family f in month t. The variable *Size Dispersion* is defined as the difference between the size of the largest and the smallest fund in the family scaled by the average size of the funds in the family. Additionally, we compute the variable *Siblings* as the natural log of the number of equity funds belonging to the same family f in month t. Finally, we use Thompson Reuters investment objective codes to identify the investment style for each fund.

1.2.2 Institutional Trading Data

We obtain trade-level data from Abel Noser Solutions/ANcerno, a consulting firm that works with institutional investors to monitor their trading costs. This database contains a detailed record of *all* executed trades since the client started reporting[5]. Previous research has shown that ANcerno institutional clients constitute approximately 8% of the total CRSP daily dollar volume (Anand et al. [18]) and that there is no survivorship or backfill bias (see, e.g, Puckett and Yan [19]).

The data is collected at the trade level and contains several variables useful for our investigation: stock identifier (*cusip*), *tradedate*, execution price, execution time, volume traded, side of the trade (i.e., buy or sell). This information is sent to Ancerno by its different clients. The identity of the clients is thereby always anonymized. Importantly, while the client is anonymized the family (called manager in Ancerno) is not. Ancerno for a limited period of time has provided a separate table including a *managercode* and a *managername* and the variables to link them to the trades. This allows us to match the Ancerno data with the CRSP Mutual Fund Database.

In particular, we hand-match fund families from ANcerno to 13f/S12 by name. There are few papers which use the management company identifier provided by ANcerno to match it with 13f companies, e.g., Franzoni and Plazzi [20], Jame [21]. However, previous papers focused only on Hedge Funds while this is the first paper to match ANcerno to mutual fund families reporting to 13f.

Our matched database spans the time interval from 1999 to 2010 and covers families including 35% to 45% of the funds in the CRSP database. Unfortunately, ANcerno did not provide us with unique fund identifies. Whether it is possible to identify funds at all using ANcerno data is debatable (from our conversations with the ANcerno support

[5]Examples of other empirical studies using ANcerno include Chemmanur et al. [17], Anand et al. [18].

team it seems that this is not possible). Therefore, we keep all the variables we obtain from ANcerno at the family level. Recently, ANcerno has decided not to provide family identifiers anymore. Hence, our data series stops at the end of 2010, since we are not able to match trades with fund families after that date.

Our main variable of interest computed from the ANcerno data is the amount of cross-trading taking place inside a mutual fund family. A cross-trade is a transaction where a buy and a sell order for the same stock coming from the same fund family is conducted by the broker without going through the open market. We identify cross-trades in our database as transactions occurring i) in the same family ii) in the same stock, iii) at the same time, iv) at the same price and having the v) the same volume in opposite directions. Figure 1 plots average commission costs for all the trades in ANcerno and the trades we identify as cross-trades. The commissions paid for cross-trades are about 1/10th of the other trades since the broker has not to look into the open market for an opposite trade but simply to record it. This result suggests that our methodology is correct. This identification solves the main concern about the cross-trade definition used in other papers based on quarterly snapshots (see e.g. Gaspar et al. [4]). Using our approach, opposite trades recorded in the same quarter but occurring on different days are *not* considered as cross-trades. Therefore, our main explanatory variable $CT_{i,t}$ is computed as the dollar volume of cross-trades executed by family f in month t over its total dollar volume of trades in the same month.

1.2.3 Summary Statistics and Additional Variable Definitions

Table 1 presents summary statistics over time. Panel A shows the sample of mutual funds before matching the families with Ancerno data. The average number of funds per month ranges from a maximum of 1799 to a minimum of 775. These funds are managed by between 225 and 135 different mutual fund management companies. The average and median mutual fund size significantly increases over time. While the average fund size was around USD 1 billion in 1999 it increased to nearly USD 1.9 billion in 2010.

Matching our sample of mutual funds to the ANcerno data decreases our sample size significantly. On average our matched sample contains between 20% and 25% of the mutual fund families from Panel A. Having between 36 and 49 families and 357 and 709 different mutual funds provides however a sample sufficient to conduct our empirical tests. Importantly, our sample is biased toward large families since the smallest families are less likely to buy ANcerno's services (this bias has been recognized also by previous studies see, e.g, Puckett and Yan [19]). In particular, our final sample contains observations from 8 out of the 10 largest mutual fund families is the United States[6]. However, since the top 10 families hold around 70% of the assets managed by the whole mutual fund industry, the bias toward larger institutions does not seem to compromise the validity of our analysis.

Table 2 presents summary statistics for the variables used in our empirical tests. Panel A shows fund level variables and Panel B displays family level variables. in total we match 206 families out of which 127 cross-trade at least one time. The most important variable for our analysis is the cross-trading variable CT. In total we classify 732434 separate trades as cross-trades The average monthly cross-trading volume per family is 0.0135% of the total monthly trading volume. This number is small, but mainly driven by the fact that a large fraction of families are not engaging in any cross-trade activity. For more than 75% of all our family-month observation the variable CT is equal to zero.

Panel B of Table 2 also contains the so far undefined variable $Weak\ Governance$. In several of our tests we study the relationship between cross-trading and the governance of the mutual fund family. For this purpose we search in the Internet and in the SEC filings whether a family was involved in any kind of SEC litigation. Panel B of Table 2 shows that 36.8 of all our observations comes from families involved in a SEC investigation.

[6]Given the non-disclosure agreement we signed with ANcerno we are forbidden to reveal the exact names of the management companies contained in our sample.

1.3 Empirical Results

1.3.1 The cross-section of cross-trades

Cross-trading is the practice where buy and sell orders for the same stock coming from the same fund family are offset by the broker without going through the open market. Cross-trades are permitted under rule 17a-7 of the U.S. Investment Company Act provided that i) such transactions involve securities for which market quotations are readily available, ii) transactions are effected at the independent current market prices of the securities, and iii) the "current market price" for certain securities[7] is calculated by averaging the highest and lowest current independent bid and offer price determined on the basis of a reasonable inquiry. Yet, some discretion may be in order when determining the "current market price[8]".

This section studies how family characteristics and time-series variation in mutual fund industry regulations affect cross-trading activity. In particular, if cross-trades are used to shift performance, we would expect the following variables to be correlated with a family's cross-trading activity.

Previous literature suggests that fund proliferation is used as a marketing strategy to attract new clients (Massa [22]) and a large number of funds in a family allows families to manage their funds like internal capital markets shifting performance across funds with similar holdings and investment styles. The first explanatory variable used in our analysis is therefore the number of funds in a family (*Siblings*). We also include a mutual fund family's size in our regressions (*Family Size*). The high correlation of *Family Size* and *Siblings* (above 90%) potentially creates problems due to multicollinearity concerns.

The next variable we use is *Weak Governance*, a dummy equal to 1 for families involved in a SEC litigation case and equal to zero otherwise. We conjecture that families having

[7] E.g., municipal securities.

[8] From our talks with compliance officers and professionals in large fund families, we understand that the pricing of cross- trades is considered one of the most relevant and critical compliance issues. Yet these trades are usually checked only with a delay and a cross-trade is considered "suspicious" only if the recorded execution price strongly deviates from the average between the bid and the ask.

been engaged in suspicious practices in the past are on average more likely to lack the necessary control mechanisms to detect and avoid illegal cross-trading activity.

Chaudhuri et al. [6] argue that an asymmetry of "product" size allows to take away relatively minor performance from larger funds to enhance substantially the performance of smaller funds. In line with this argument we include the variable *Size Dispersion* in our regressions.

Nanda et al. [7] empirically show that a strategy of some mutual fund families is to start a large number of funds with different strategies to increase the chances to create a "star fund", i.e., a fund whose performance ranks high among its peers. Such families have on average a higher intra-family return dispersion (*Return Dispersion*). We conjecture that families following the aforementioned strategy are also more likely to use cross-trades in order to increase the performance of specific funds in the family.

Finally, we study governance not only in the cross-section, but also in the time-series. An exogenous change in the regulatory environment forcing management companies to improve their governance was triggered by the late trading scandal. On September 3, 2003 the New York State Attorney General Eliot Spitzer announced the issuance of a complaint claiming that several mutual fund firms had arrangements allowing trades that violated terms in their funds' prospectuses, fiduciary duties, and securities laws. Subsequent investigations showed that at least twenty mutual fund management companies, including some of the industry's largest firms, had struck deals permitting improper trading (McCabe [23]).

As a consequence of the scandal, in 2004 the SEC adopted new rules requiring fund families to adopt more stringent compliance policies. In particular, Rule 38a-1 under the Investment Company Act of 1940 required each fund to appoint a chief compliance officer responsible for administering the fund's policies and procedures. Additionally, compliance officers have to report directly to the board of directors to increase their independence. The compliance date of the new rules and rule amendments was October 5, 2004. From our talks with compliance officers at one of the largest management companies, we understood that one of the main tasks of the compliance officer is to check that the execution price of the cross-trades is within a "reasonable" range from the mid price of the day.

This regulatory change makes it, on the one hand, more difficult for fund families to misprice cross-trades. On the other hand, if performance shifting was the main rationale for crossing trades within the family, the new regulation reduces the incentive for cross-trading activity. To capture a potential decrease in cross-trading activity we define a dummy variable equal to one for observations after 2003

Table 3 presents results from pooled regressions of cross-trading activity on the above-mentioned variables. Observations are at the month-family level and all standard errors are clustered at the time level. In columns (1)-(6) of Table 3 we first run univariate regressions using the different family characteristics and, to capture the regulatory change in 2004, the dummy equal to one for observations after 2003. Our results indicate that families with many siblings, weak governance, high size and return dispersion, and a large family size have exhibit significantly higher cross-trading activity. This result is in line with the hypothesis that mutual fund families use cross-trades to actively shift performance between different funds in the family. Additionally, the average amount of cross-trading significantly drops (by roughly 8.4 basis points) after the late trading scandal. Hence, the new compliance policy was effective at the very least in limiting the amount of cross-trading activity.

In column 7 we run multivariate regressions. While most of the coefficients stay significant and have similar magnitudes as in the univariate regressions, the effect of $Siblings$ on the amount of cross-trading becomes ambiguous. The estimated coefficient is positive and significant in column 1. After controlling for other family characteristics however, the sign changes in column 7. This finding is probably driven by the high correlation between $Siblings$ and $FamilySize$.

In Figure 2 we plot the average amount of cross-trading across time. The figure shows clearly that the decrease in cross-trading is not a trend but starts around the late trading scandal. In particular, cross-trading activity drops significantly after the new regulation's compliance date.

1.3.2 The Pricing of Cross-Trades

Cross-trading is legal when it occurs at reasonable market prices and does not benefit one counterparty over the other. Conversely, cross-trading shifts performance when one party buys (or sells) at a discount (or at a premium). In Table 4 we regress the absolute percentage deviation of the execution price from the VWAP on family characteristics. If cross-trades were correctly priced we should not observe significant deviations from the VWAP. Additionally, family characteristics should not matter on how cross-trades are priced. Here only one leg of the cross-trades is included in the sample, e.g., only the buy side (since the sell side of the cross-trades is executed at the same price, running our regressions only on the sell side would give exactly the same results). In our regressions we use the same explanatory variables as before. We do not include stock level controls since characteristics that normally have an effect on the execution price (such as stock illiquidity, price impact, past return) should be of no importance when the trade is not executed in the open market. Our regressions are now at the trade level and include *only* cross-trades. Day fixed effects are included and errors are clustered at the day level.

Almost all variables that predict a larger amount of cross-trading activity also predict higher mispricing in the execution price. Families with weak governance, more assets to manage, and large fund size dispersion execute cross-trades at prices far away from the average of the market during the day for that particular stock (the coefficient of *Return Dispersion* is however not significantly different from zero). This result strongly suggests that cross-trades executed within such families "move" performance. Additionally, after the late trading scandal, the average deviation from the VWAP drops by 36 basis points (see also Figure 3). Results in this section suggest that cross-trading shifts performance between funds. However, we cannot tell whether cross-trades are use to shift performance to the most valuable funds or smooth performance across all funds in the family.

1.4 Star funds, cross-trading and performance shifting

1.4.1 Methodology

In this section we explore whether fund families use mispriced cross trades as a tool for shifting performance toward the most valuable funds or smooth performance across the family.

On the one hand, the work of Nanda et al. [7] suggests that there is a clear incentive for a mutual fund family to improve the performance of good performing funds with high inflows. Nanda et al. [7] find that funds rated as "star" funds by the popular Morningstar rating experience significant inflows and they have a positive spill-over effect on other funds in the family. Specifically, also other funds in the family have higher inflows when there is one "star" fund in the family. On the contrary, a bad performing fund in the family does not seem to have any negative effect on the flows to rest of the family. Flows are of particular importance in the mutual fund industry since revenues are usually a fixed part of the asset under management, i.e., performance fees are uncommon (Haslem [24]). Hence, in order to maximize fees at the family level performance shifting via cross-trades can be an optimal strategy for a fund family.

On the other hand, cross-trades can be used by the family to provide liquidity to underperforming funds to decrease the performance consequences of large investor redemptions. This strategy would be optimal when a severe underperformance of a fund has a negative impact on the other members of the family that is greater than the cost of providing coinsurance. Goncalves-Pinto and Sotes-Paladino [5], Bhattacharya et al. [8] and Schmidt and Goncalves-Pinto [9] provide support for this hypothesis.

The two alternative hypotheses mentioned above have opposite empirical predictions. According to the favoritism hypothesis, cross-trading should increase the gap in the performance between the most important funds and the least important funds in the family. Conversely, the performance smoothing hypothesis predicts that cross-trading reduces the spread in their performance. Importantly, according to the law cross-trading could decrease trading costs and, hence, improve funds' performance. However, it should not be systematically correlated with the gap in the performance between high and low value funds.

It is important to highlight again that due to the structure of our data we are not able to identify the funds on both sides of a cross-trade, i.e. we are not able to pinpoint which funds in the family are trading with each other. Our empirical strategy is therefore first to define groups of funds inside a family which we hypothesize are likely to benefit or suffer from cross-trading if a fund family strategically shifts performance. Afterwards, we test whether the difference in their returns correlates with cross-trading activity drawing from the methodology of Gaspar et al. [4].

Specifically, in our main tests we rank funds according to their monthly flows (see, e.g., Bhattacharya et al. [8]). The reason for ranking funds according to their flows is intuitive. Funds with outflows are liquidity demanders and funds with inflows are the natural liquidity suppliers. On the one hand, under a performance smoothing family strategy the liquidity suppliers can buy at inflated prices securities from the liquidity demanding funds thereby increasing the performance of the outflow funds while decreasing their own performance. On the other hand, the liquidity supplying funds can buy at deflated prices securities from the liquidity demanding funds increasing the performance of the inflow funds. Besides ranking funds according to their flows, in some of our tests we also rank funds according to their fees following Gaspar et al. [4].

Having ranked the funds, we sort them inside a family into terciles[9]. Funds that display intermediate flows are discarded. From the two extreme terciles we construct pairwise combinations of funds from the top and the bottom terciles and we compute the spread in their style adjusted performance (4-factor alpha). In order to control for style effects we impose as an additional restriction that the funds operate in the same investment style.

For instance, consider a family having 6 funds with the same investment style and assume that in month t, the funds have all different flows. This implies a ranking from 1 to 6 and two funds in each tercile. For our analysis we discard the funds ranked third and fourth and we build the return spread from the remaining funds. Specifically, the observations

[9] Using quintiles gives similar results.

in our final sample are the difference of performance between fund 5 and fund 1; fund 5 and fund 2; fund 6 and fund; fund 6 and fund 2.

To understand whether cross-trading smoothes performance across the family or shifts performance to the most valuable funds, we regress the spread in performance between funds in the top tercile and bottom tercile on different measures of cross-trading activity controlling for family characteristics and observable differences between the two funds. Formally,

$$Spread_{i,j,t} = \beta(CT_{f,t}) + Controls_{i,j,t} + \theta_t + \epsilon_{i,j,t},$$

where *spread* is the difference between the high value fund i and the low value fund j's raw performance (or 4 factor alpha) in month t conditional on having the same investment style and belonging to the same fund family. θ_t are month fixed effects and $CT_{f,t}$ is the cross-trading measure.

The average *spread* will be positive since on average funds with higher flows (fees) outperform funds with lower flows (fees). However, under the null hypothesis of no strategic interaction, we should not expect a statistically significant correlation between the spread in performance and CT. Under the favoritism hypothesis we should expect a positive correlation between the spread and CT (i.e., favoritism increases the performance of the high value funds at the expense of the low value siblings). Under the performance smoothing hypothesis we should expect a negative coefficient (i.e., families smooth performance, decreasing the gap in performance between high and low value funds).

1.4.2 Favoritism versus Performance Smoothing

In Table 5 we study the effect of cross-trading activity on the performance spread between high flow and low flow funds inside each family. We report results for the spread in style adjusted returns (columns 1-4) and for the spread in 4-factor alphas (columns

5-8). All of our regressions include time fixed effects and we cluster errors at the time level[10].

The correlation between CT and *spread* is positive and strongly significant. This result suggests that cross-trades favor the high inflow funds at the expenses of low inflow funds inside the family and does not support the performance smoothing hypothesis. Controlling for a number of control variable does change the results qualitatively. In column 2 and 6 we include $Family\ Size$ in the regressions to control for the significant relation between cross-trading and family size[11]. In columns 3 and 7 we include a number of fund level controls. Specifically, to ensure that our results are not driven by differences in characteristics between the two funds in a spread portfolio we include their size difference ($\Delta Size$), their return difference in the previous month ($\Delta Returns$) and the their flow difference in the previous month ($\Delta FLow$). The results suggest that fund level differences are of no statistical importance. Finally, we also include the family level variables $Size\ Dispersion$ and $Return\ Dispersion$ in the regressions. Columns 4 and 8 suggest that $Size\ Dispersion$ and $Return\ Dispersion$ not only have a positive impact on cross-trading activity, but also independently predict a higher difference in returns between high value funds and low value funds.

We consider different specifications of our main test. First, instead of using the cross-trading activity CT as a regressor we use the value-weighted mispricing of cross-trades. Potentially, our previous results would be consistent also with a big spread in performance between high and low value siblings triggering higher cross-trading activity. In order to show that cross-trades have a causal effect on the performance spread, we want to show that a higher mispricing of the cross-trades is associated with a larger performance gap. To obtain this explanatory variable we first compute the mispricing of each cross-trade as the difference between the execution price and the VWAP of the day. Afterwards we aggregate the mispricings for each family in each month by weighting the different cross-trades by their dollar size. Hence, a family whose cross-trades are on average priced far away from the VWAP have a higher value of our variable "value-weighted

[10] Clustering errors at the fund pair level or including fund-pair fixed effects does not influence the results.

[11] We use family size and not the number of siblings. Using *Siblings* as a regressor does not change the results.

mispricing". The results in Table 6 suggest a positive effect of value-weighted mispricing on the performance spread between high flow funds and low flow funds. Again, this results supports the hypothesis of a family strategy which shifts performance to the most valuable funds.

Second, we sort funds according to their fees instead of their flows. Gaspar et al. [4] argue that high fee funds are more valuable to the family as they generate more fee income. Hence, families can use cross-trades to increase the performance and the subsequent flows of high fee funds. And indeed, the results in Table 7 support this hypothesis. Although the results are economically weaker, there is a statistically significant relationship between the amount of cross-trading inside the family and the performance spread between high fee funds and low fee funds inside a mutual fund family.

Overall, our empirical results are consistent with the hypothesis that mutual fund families use cross-trades to shift performance to their most valuable funds. In families where cross-trading activity is high, the spread in performance between popular and unpopular funds is greater.

In the next section we study whether the performance implications of cross-trading vary systemically with proxies for fund governance in the time-series and cross-section.

1.4.3 Governance

Drawing from our analysis in Section 3 we study in this section the impact of differences in mutual fund governance on the performance spread between high value funds and low value funds. We start by analysing the impact of the regulatory change due to the mutual fund late trading scandal.

In Table 8 we therefore divide the sample into a pre-2003 period and a post-2003 period and run our analysis separately on the two different samples. The results in Table 8 show that the coefficients for the effect of CT on the spread of the performance between high and low value funds are 10 times smaller after the late trading scandal and not statistically significant. Figures 2 and 3 show that the amount of cross-trading as well as the mispricing of cross-trades dropped significantly after the scandal (i.e., it is not just a trend). Interestingly, the mispricing of the cross-trades increases again around the financial crisis. This finding suggests that the value of shifting performance to "rescue" the important funds in the family during the crisis was higher than the cost of "being caught".

In particular, concerning the anecdotal evidence reported in the introduction about the legal action of the Security and Exchange Commission against Western Asset Management, the SEC discovered that most of the (allegedly) illegal cross-trading activity took place during the financial crisis. This seems consistent with our findings.

In Table 9 instead of analysing the relation between mutual fund governance changes in the time-series and the performance spread, we examine cross-sectional differences in governance using our previously defined variable $Weak\ Governance$. Columns 1 to 4 show results for the sample of mutual funds where the value of $Weak\ Governance$ is equal to 1, whereas columns 5 to 8 show results for the sample of mutual funds where the value of $Weak\ Governance$ is equal to 0. Consistent with the hypothesis that predation is stronger in families where governance is weak, we find our results to be entirely driven by sample of mutual funds with weak governance.

1.5 Robustness

In this section we provide additional evidence supporting the validity of our results. A potential issue with our results in Table 5 is that, given that the distribution of the CT variable is highly skewed, the correlation between CT and *spread* could be driven by some outliers. To rule out this concern in Table 10 we replicate our empirical design using as main explanatory variable a dummy variable taking value of 1 when there is at least a cross trade in family f and month t, and equal to zero otherwise . We find the gap in performance between high and low value funds to be 42 basis points (17 basis point considering risk-adjusted returns) higher in families that cross-trade. This excludes that our results are driven by outliers.

Another potential problem with our main methodology explained in Section 4 arises from using as dependent variable in our regressions the spread in the performance between high value and low value funds. In this way we cannot rule out that the correlation between CT and the performance spread is driven only by one of the two parties of the transaction. If that was the case, our results would be inconsistent with performance shifting through cross-trading.

Hence, in Table 11 we replicate our regressions without matching funds. In particular, all funds are divided in terciles according to the distribution of flows in the current month. Funds displaying intermediate flows in month t are dropped. Hence, we create two separate sub-samples. The first one containing only high-flow funds, the second one only low-flow funds. In this way each sample contains only funds with relatively similar contemporaneous flows.

Using this alternative methodology we do not need to impose that a family has at least three funds to be included in our sample. Hence, our sample is much bigger containing 206 fund families and 1397 funds.

Results in columns 1 and 2 suggest that the performance of high value funds positively correlates with the amount of cross-trades executed within their own family. Coefficients reported in column 3 and 4 show that the performance of low value funds is negatively correlated with the amount of cross-trades. Importantly coefficients are almost symmetric. This result is consistent with the hypothesis that performance is shifted from outflow to inflow funds through cross-trading.

Additionally, in Table 12 we replicate the results reported in Table 5 using lagged CT as the main independent variable. Results stay unchanged. This finding relaxes concerns about reverse causality bias. In particular, we want to rule out that a high spread in performance triggers cross-trading activity. Consistent with a causal effect of CT on performance, our results do not change when we explore the effect of past cross-trading activity on present spread.

1.6 Conclusion

In this paper, we explore the extent of cross-trading activity in mutual fund families and its impact on fund performance. Previous proxies of cross-trades used in the literature rely on quarterly holdings which makes a precise identification of cross-trades impossible. To overcome this issue we exploit institutional trade level data provided by Ancerno. In order to consider two opposite trades as a cross-trade, we require that the trades come from funds belonging to the same fund family, are in the same stock, involve the exact same quantity of shares traded, and share the same execution day, time and price. That provides us with a much more reliable identification of cross-trades in mutual fund families.

Using this measure, we document that cross-trading activity is particularly high in large and weak governance families with high fund size dispersion and before 2003. The same families that cross-trade more are also more likely to cross-trade at prices unfairly far from the VWAP of the day (up to a deviation of 2% per trade). This mispricing has a significant impact on performance. We find that "star" funds performance in family that cross-trade is boosted by 2.5% per year (1% risk adjusted), while the performance of the less valuable funds is reduced by the same amount. Since average monthly risk-adjusted performance in our sample is slightly negative and non-statistically different from zero, this behavior has obviously important implications for fund ranking, fund selection and fund manager evaluation.

Mutual fund families have a fiduciary duty to treat all their clients equally. Using cross-trading activity to favor the most valuable siblings makes economic sense since outperforming funds attract disproportionate flows and have spillover effects on the other affiliated funds. However, this practice breaches fiduciary duties toward investors since severely hurts the performance of the less valuable funds in the family. Additionally, our results suggest that fund alphas significantly misrepresent the real ability of fund managers to create value for their investors. Studies on fund manager skill as well as investors choosing where to allocate their money should consider the extent of cross-trading activity and its impact on performance in their analyses. Finally, we find that governance is highly effective in reducing unfair cross-trading activity. In particular, both cross-sectional and time series variations in family governance suggest that better governance is associated with less cross-trading and lower mispricing.

Table 1.1: **Summary Statistics**

This table provides summary statistics over time for the CRSP Mutual fund database and the CRSP-Ancerno matched sample. All the variables are annual averages of monthly averages. Funds is the number of funds, Fund Size and Family Size are measured in USD millions, Families is the number of families, Siblings is the number of funds in a family.

CRSP Mutual Fund Database							
		Fund Size				**Family Size**	
Year	**Funds**	**Mean**	**Median**	**Siblings**	**Families**	**Mean**	**Median**
1999	1789	1082	115	8	224	8647	1402
2000	1799	1285	140	9	223	10387	1634
2001	1698	1136	142	8	213	9061	1463
2002	1634	1005	135	8	205	8031	1341
2003	1542	1012	145	8	195	7995	1312
2004	1457	1324	193	8	185	10403	1718
2005	1370	1525	212	8	177	11785	1929
2006	1297	1718	231	8	167	13334	2193
2007	1187	2050	277	8	155	15658	2534
2008	1138	1805	239	8	150	13679	2200
2009	971	1426	201	8	144	9608	1617
2010	775	1897	266	8	135	10921	1813
Ancerno-Crsp Match							
1999	619	1846	148	14	46	24715	2529
2000	709	1842	163	14	55	23779	3094
2001	587	1729	178	15	43	23806	2636
2002	655	1615	191	14	48	21924	3142
2003	666	1493	197	14	49	20139	3289
2004	638	1953	274	14	49	25656	4109
2005	611	2097	339	13	49	26484	4385
2006	579	2271	370	13	46	28816	4373
2007	541	2629	445	13	42	33841	7143
2008	498	2370	403	14	38	31321	7604
2009	451	1771	354	13	38	20929	5015
2010	357	2362	491	13	36	23175	5442

TABLE 1.2: **Summary Statistics for fund-level and family-level regression**

This table provides summary statistics for the pooled sample. Panel A shows fund level variables and Panel B family level variables. Size is fund size measured in USD millions, Excess return is fund return minus the risk-free rate, Alpha is the risk-adjusted return using the Carhart [15] four factor model, Fees are annual fund fees defines as $ExpenseRatio + 1/7 * (FrontLoad + RearLoad)$, Flow is monthly flow defined as $\frac{AUM(t) - AUM(t-1)*(1+ret)}{AUM(t-1)}$, CT is the family volume of cross-trades in USD divided by the family's monthly trading volume in USD. *Siblings* is the number of funds in the family, *Weak Governance* is a dummy variable equal to 1 if the family was involved in a litigation for practices potentially hurting mutual fund clients at any point in time, *Size* dispersion is the size difference between the largest and the smallest fund in the family divided by the average fund size in the family, *Return Dispersion* is the monthly cross-sectional return standard deviation inside the family, *Family Size* is assets under management of the family in USD millions.

	Mean	**Stdev**	**Percentiles**				
			10	**25**	**50**	**75**	**90**
Panel A: Fund Level Summary Statistics							
Size	1,688	5,687	9.600	44.90	222.7	940.5	3,379
Excess Return	0.00168	0.0554	-0.0641	-0.0258	0.00435	0.0321	0.0626
Alpha	0.000233	0.0231	-0.0229	-0.00990	-0.000330	0.00953	0.0238
Fees	0.0134	0.00647	0.00580	0.00910	0.0128	0.0177	0.0221
Flow(t)	0.00291	0.0606	-0.0360	-0.0170	-0.00492	0.0100	0.0419
Panel B: Family Level Summary Statistics							
CT	0.00143	0.00950	0	0	0	0	0.000135
Return Dispersion (t-1)	0.0167	0.0115	0.00549	0.00893	0.0142	0.0216	0.0304
Siblings(t-1)	11.20	14.01	3	4	7	13	23
Family Size(t-1)	18,141	58,443	190.3	582.9	2,334	9,248	35,894
Size Dispersion(t-1)	3.827	2.938	1.207	1.919	2.976	4.736	7.734
Weak Governance	0.368	0.482	0	0	0	1	1

TABLE 1.3: **The cross-section of cross-trading activity**

This table presents results of cross-sectional regressions studying the relationship between monthly cross-trading activity, fund family characteristics and time-series changes in the mutual fund regulation. The dependent variable is a family's monthly volume of cross-trades in USD divided by the family's monthly trading volume in USD. *Siblings* is the (log) number of funds in the family, *Weak Governance* is a dummy variable that takes value one if a family was involved in a litigation for practices potentially hurting mutual fund clients at any point in time, *Size* dispersion is the lagged size difference between the largest and the smallest fund in the family divided by the average fund size in the family, *Return Dispersion* is the lagged monthly cross-sectional return standard deviation inside the family, *Family Size* is the log of assets under management of the family in USD millions in month t-1, *Post*2003 is a dummy variable equal to one after 2003. Standard errors are clustered at the month level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Siblings	0.00294***						-0.00185***
	(16.62)						(-9.025)
Weak Governance		0.00192***					0.000781***
		(8.938)					(4.140)
Size Dispersion			0.00111***				0.00145***
			(17.26)				(13.93)
Return Dispersion				0.0570***			0.0125*
				(6.142)			(1.664)
Family Size					0.00103***		0.000113*
					(17.47)		(1.661)
Post2003						-0.000843***	
						(-5.819)	
Constant	-0.00457***	0.000721***	-0.00283***	0.000481***	-0.00665***	0.00186***	-0.00177***
	(-12.67)	(9.145)	(-11.47)	(3.108)	(-14.38)	(16.40)	(-5.339)
Time Fixed Effects	Y	Y	Y	Y	Y	N	Y
Observations	9,343	9,343	9,343	9,184	9,329	9,343	9,170
R-squared	0.070	0.019	0.127	0.014	0.058	0.002	0.135

Table 1.4: **The cross-section of mispricing**

This table presents results of cross-sectional regressions studying the relationship between the mispricing of cross-trades, fund family characteristics and time-series changes in mutual fund regulation. **Only** cross-trades are included. The dependent variable is the mispricing of a cross-trade defined as the absolute deviation of a cross-trades execution price from volume-weighted average price of the day (VWAP). *Siblings* is the (log) number of funds in the family, *Weak Governance* is a dummy variable that takes value one if a family was involved in a litigation for practices potentially hurting mutual fund clients at any point in time, *Size* dispersion is the lagged size difference between the largest and the smallest fund in the family divided by the average fund size in the family, *Return Dispersion* is the lagged monthly cross-sectional return standard deviation inside the family, *Family Size* is the log of assets under management of the family in USD millions in month t-1, *Post*2003 is a dummy variable equal to one after 2003. Standard errors are clustered at the month level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Siblings	0.0007***						-0.0005
	(8.37)						(-1.21)
Weak Governance		0.0014***					0.0012***
		(7.42)					(3.52)
Size Dispersion			0.0001***				0.0001*
			(7.67)				(1.80)
Returns Dispersion				0.0487***			-0.0062
				(3.57)			(-0.34)
Family Size					0.0003***		0.0002**
					(7.17)		(2.41)
Post 2003						-0.0036***	
						(-13.20)	
Constant	0.0061***	0.0079***	0.0072***	0.0073***	0.0057***	0.0105***	0.0061***
	(18.55)	(65.63)	(35.08)	(16.87)	(13.16)	(65.72)	(9.08)
Time Fixed Effects	Y	Y	Y	Y	Y	N	Y
Observations	366,217	366,217	366,217	366,147	366,217	366,217	366,147
R-squared	0.216	0.216	0.216	0.215	0.216	0.032	0.216

TABLE 1.5: **Favoritism versus Performance Smoothing**

This table presents results for regressions of *spread* on *CT* and controls. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. *CT* is computed as the percentage of cross-trades in family f in month t. The independent variables are: *FamilySize*, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; *Size Dispersion*, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; *Returns Dispersion*, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.2749***	0.1796***	0.1777***	0.1464***	0.1712***	0.0971***	0.0956***	0.0640***
	(8.88)	(5.62)	(5.44)	(4.13)	(9.63)	(5.07)	(5.04)	(2.92)
Family Size		0.0021***	0.0021***	0.0011***		0.0017***	0.0017***	0.0007***
		(9.14)	(8.65)	(3.81)		(8.35)	(8.80)	(2.96)
Δ Size			-0.0006*	-0.0006*			-0.0002	-0.0002
			(-1.95)	(-1.95)			(-1.63)	(-1.63)
Δ Returns			0.0215	0.0187			0.0025	-0.0000
			(0.33)	(0.29)			(0.12)	(-0.00)
Δ Flows			-0.0164**	-0.0165**			-0.0142***	-0.0143***
			(-1.99)	(-2.00)			(-2.99)	(-3.01)
Returns Dispersion				0.2821***				0.2523***
				(4.10)				(5.25)
Size Dispersion				0.0003*				0.0003**
				(1.75)				(2.40)
Constant	0.0071***	-0.0145***	-0.0142***	-0.0119***	0.0050***	-0.0118***	-0.0116***	-0.0089***
	(11.24)	(-5.98)	(-6.01)	(-4.97)	(13.81)	(-5.68)	(-5.78)	(-5.09)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	106,220	106,123	105,734	105,640	106,220	106,128	105,734	105,640
R-squared	0.121	0.125	0.125	0.127	0.057	0.062	0.064	0.066

TABLE 1.6: **Mispricing of cross-trades and fund returns**

This table presents results for regressions of *spread* on $Value - weightedMispricing$ and controls. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. $Value - weightedMispricing$ is computed as the tradesize weighted average of absolute deviations of cross-trades' execution prices from volume-weighted average prices in family f in month t. The independent variables are: $FamilySize$, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; $Sizedispersion$, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; $ReturnDispersion$, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value weighted Mispricing	1.3713***	0.6379***	0.6236***	0.4434***	0.8499***	0.3134***	0.3123***	0.1819*
	(7.71)	(4.36)	(4.31)	(3.58)	(6.92)	(2.92)	(2.92)	(1.89)
FamilySize		0.0031***	0.0031***	0.0006*		0.0022***	0.0022***	0.0004*
		(11.70)	(11.31)	(1.90)		(11.55)	(12.07)	(1.88)
Δ Size		-0.0005*	-0.0006*	-0.0006*			-0.0002	-0.0002
		(-1.72)	(-1.86)	(-1.88)			(-1.55)	(-1.56)
Δ Returns			0.0232	0.0185			0.0038	0.0002
			(0.35)	(0.28)			(0.17)	(0.01)
Δ Flows			-0.0173**	-0.0172**			-0.0146***	-0.0146***
			(-2.09)	(-2.08)			(-3.06)	(-3.06)
Returns Dispersion				0.3076***				0.2606***
				(4.30)				(5.35)
Size Dispersion				0.0008***				0.0006***
				(5.41)				(5.54)
Constant	0.0079***	-0.0236***	-0.0230***	-0.0109***	0.0055***	-0.0171***	-0.0168***	-0.0084***
	(13.30)	(-8.06)	(-8.13)	(-4.65)	(13.37)	(-8.23)	(-8.41)	(-4.83)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	109,233	109,128	108,739	108,645	109,233	109,141	108,739	108,645
R-squared	0.107	0.121	0.119	0.123	0.047	0.059	0.061	0.065

TABLE 1.7: **Sorting on fees**

This table presents results for regressions of *spread* on CT and controls. Each observation is obtained from the pairwise combinations of high-fee funds with low-fee funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of high-fee fund i (i.e., funds with fees in the top tercile of family f in a given month t) minus low-fee fund j's return (4-factor alpha), i.e., funds with fees in the bottom tercile of family f in a given month t. Funds with fees in the intermediate tercile are dropped. CT is computed as the percentage of cross-trades in family f in month t. The independent variables are: $FamilySize$, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; $Sizedispersion$, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; $ReturnDispersion$, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.0399	0.0478*	0.0422	0.0497*	0.0345**	0.0394***	0.0382**	0.0334*
	(1.54)	(1.83)	(1.53)	(1.73)	(2.55)	(2.61)	(2.51)	(1.96)
FamilySize		-0.0002	-0.0003*	-0.0001		-0.0001	-0.0001	-0.0003
		(-1.19)	(-1.92)	(-0.28)		(-0.80)	(-1.09)	(-1.33)
Δ Size			-0.0003	-0.0003			-0.0001	-0.0001
			(-1.48)	(-1.52)			(-0.91)	(-0.89)
Δ Returns			0.0393	0.0392			0.0203	0.0203
			(0.53)	(0.53)			(0.88)	(0.88)
Δ Flows			0.0003	0.0003			-0.0021	-0.0022
			(0.03)	(0.03)			(-0.45)	(-0.46)
Returns Dispersion				0.0701				0.0300
				(1.05)				(0.58)
Size Dispersion				-0.0002				0.0001
				(-1.36)				(0.48)
Constant	0.0006	0.0024	0.0031**	0.0010	-0.0003	0.0008	0.0011	0.0016
	(1.24)	(1.48)	(2.15)	(0.65)	(-1.17)	(0.58)	(0.78)	(1.20)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	108,350	108,330	107,833	107,739	108,350	108,330	107,833	107,739
R-squared	0.023	0.023	0.025	0.025	0.019	0.019	0.020	0.020

TABLE 1.8: **Late Trading Scandal**

This table presents results for regressions of *spread* on CT and controls for different sub-samples. Specifically, the sample is divided into a pre 2003 period and a post 2003 period. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. $CT_{t,f}$ is computed as the percentage of cross-trades in family f in month t. The independent variables are: $FamilySize$, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; $Sizedispersion$, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; $ReturnDispersion$, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Pre Late Trading Scandal				**Post Late Trading Scandal**			
	Spread of Style adj. returns		Spread of 4-factor alpha		Spread of Style adj. returns		Spread of 4-factor alpha	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.2273***	0.2040***	0.1359***	0.1065***	0.0330	0.0278	0.0135	0.0104
	(5.69)	(3.63)	(6.08)	(2.70)	(0.83)	(0.67)	(0.39)	(0.28)
Family Size	0.0014***	0.0013***	0.0009**	0.0006**	0.0025***	0.0011***	0.0021***	0.0007**
	(3.21)	(3.10)	(2.66)	(2.40)	(10.24)	(2.75)	(9.05)	(2.02)
Δ Size	-0.0009*	-0.0009*	-0.0003	-0.0003	-0.0001	-0.0001	-0.0001	-0.0001
	(-1.79)	(-1.81)	(-1.63)	(-1.67)	(-0.79)	(-0.73)	(-0.52)	(-0.47)
Δ Returns	0.0145	0.0132	0.0076	0.0065	0.0349	0.0303	-0.0115	-0.0166
	(0.16)	(0.14)	(0.28)	(0.25)	(0.67)	(0.58)	(-0.29)	(-0.42)
Δ Flows	-0.0144	-0.0147	-0.0119*	-0.0122*	-0.0194***	-0.0194***	-0.0173**	-0.0174**
	(-1.12)	(-1.14)	(-1.82)	(-1.85)	(-2.81)	(-2.81)	(-2.55)	(-2.56)
Returns Dispersion		0.2848***		0.2245***		0.1792**		0.2298***
		(2.71)		(2.66)		(2.57)		(3.52)
Size Dispersion		-0.0001		0.0001		0.0005***		0.0004**
		(-0.18)		(0.39)		(2.97)		(2.53)
Constant	-0.0056	-0.0103**	-0.0042	-0.0068**	-0.0192***	-0.0123***	-0.0161***	-0.0095***
	(-1.31)	(-2.49)	(-1.18)	(-2.12)	(-7.33)	(-4.01)	(-6.58)	(-3.71)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	51,351	51,333	51,351	51,333	54,383	54,307	54,383	54,307
R-squared	0.141	0.142	0.066	0.067	0.067	0.069	0.056	0.059

Table 1.9: **Governance**

This table presents results for regressions of *spread* on *CT* and controls for different sub-samples. Specifically, the sample is divided into a sample of weak governance families and a sample of strong governance families. A mutual fund family is assumed to have weak governance if it was involved in a legal litigation at any point in time. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. $CT_{t,f}$ is computed as the percentage of cross-trades in family f in month t. The independent variables are: $FamilySize$, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; $Sizedispersion$, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; $ReturnDispersion$, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

Governance	**Weak**				**Strong**			
	Spread of Style adj. returns		Spread of 4-factor alpha		Spread of Style adj. returns		Spread of 4-factor alpha	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT	0.1911***	0.1561***	0.1911***	0.1561***	0.0127	0.0050	0.0289	0.0237
	(5.21)	(4.18)	(5.21)	(4.18)	(0.36)	(0.14)	(0.84)	(0.66)
Family Size	0.0022***	0.0005	0.0022***	0.0005	0.0013***	0.0017***	0.0005***	0.0008***
	(6.61)	(1.15)	(6.61)	(1.15)	(4.92)	(4.84)	(3.09)	(3.68)
Δ Size	-0.0006*	-0.0006*	-0.0006*	-0.0006*	-0.0004**	-0.0004**	-0.0001	-0.0001
	(-1.79)	(-1.81)	(-1.79)	(-1.81)	(-2.10)	(-2.07)	(-1.03)	(-0.99)
Δ Returns	0.0214	0.0189	0.0214	0.0189	0.0221	0.0217	0.0088	0.0079
	(0.33)	(0.29)	(0.33)	(0.29)	(0.32)	(0.31)	(0.45)	(0.40)
Δ Flows	-0.0214**	-0.0216**	-0.0214**	-0.0216**	-0.0024	-0.0021	0.0025	0.0027
	(-2.26)	(-2.28)	(-2.26)	(-2.28)	(-0.33)	(-0.30)	(0.66)	(0.72)
Returns Dispersion		0.4224***		0.4224***		0.0487		0.1137**
		(4.57)		(4.57)		(0.74)		(2.12)
Size Dispersion		0.0004**		0.0004**		-0.0004*		-0.0004**
		(2.07)		(2.07)		(-1.78)		(-2.21)
Constant	-0.0149***	-0.0098***	-0.0149***	-0.0098***	-0.0071***	-0.0094***	-0.0016	-0.0049**
	(-4.78)	(-3.13)	(-4.78)	(-3.13)	(-2.71)	(-3.25)	(-1.14)	(-2.55)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	77,522	77,490	77,522	77,490	28,212	28,150	28,212	28,150
R-squared	0.142	0.143	0.142	0.143	0.069	0.069	0.029	0.030

Table 1.10: **Alternative proxy**

This table presents results for regressions of *spread* on CTD and controls. CTD is a dummy variable that takes value one when a family cross-trade in month t and zero otherwise. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. Families with less than 3 funds are dropped as well. The independent variables are: $FamilySize$, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; $Sizedispersion$, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; $ReturnDispersion$, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

	Spread of Style adj. returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CT Dummy	0.0125***	0.0051***	0.0050***	0.0042***	0.0077***	0.0023**	0.0023**	0.0017**
	(7.78)	(4.31)	(4.27)	(4.01)	(7.02)	(2.42)	(2.46)	(2.00)
Family Size		0.0032***	0.0032***	0.0004		0.0023***	0.0023***	0.0004
		(12.45)	(11.58)	(1.35)		(11.73)	(12.04)	(1.57)
Δ Size		-0.0005*	-0.0005*	-0.0006*			-0.0002	-0.0002
		(-1.68)	(-1.83)	(-1.90)			(-1.51)	(-1.59)
Δ Returns			0.0232	0.0186			0.0035	-0.0001
			(0.35)	(0.28)			(0.16)	(-0.00)
Δ Flows			-0.0177**	-0.0172**			-0.0149***	-0.0146***
			(-2.13)	(-2.08)			(-3.10)	(-3.06)
Returns Dispersion				0.3168***				0.2671***
				(4.49)				(5.56)
Size Dispersion				0.0009***				0.0006***
				(5.48)				(5.23)
Constant	0.0079***	-0.0245***	-0.0238***	-0.0104***	0.0055***	-0.0174***	-0.0171***	-0.0083***
	(12.67)	(-8.32)	(-8.23)	(-4.32)	(13.11)	(-8.24)	(-8.34)	(-4.66)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	106,220	106,123	105,734	105,640	106,220	106,128	105,734	105,640
R-squared	0.107	0.121	0.120	0.124	0.046	0.059	0.061	0.065

Table 1.11: **Alternative methodology**

This table presents results for regressions of *excess returns* and *alphas* on *CT* and controls. Each month funds are sorted in three terciles on the basis of their contemporaneous flows. Funds displaying intermediate flows are discarded. Regressions are ran separately for funds with flows in the top tercile (Inflow funds) and in the bottom tercile (Outflow funds). The independent variables are: *Siblings* the log of the number of funds in family f in month t, $FamilySize$, the natural log of the lagged assets under management of the family; $FundSize$, the natural log of the lagged fund i total assets under management; $PastFlows$, fund i lagged flows; $PastReturns$, fund i lagged returns; $Sizedispersion$, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; $ReturnDispersion$, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

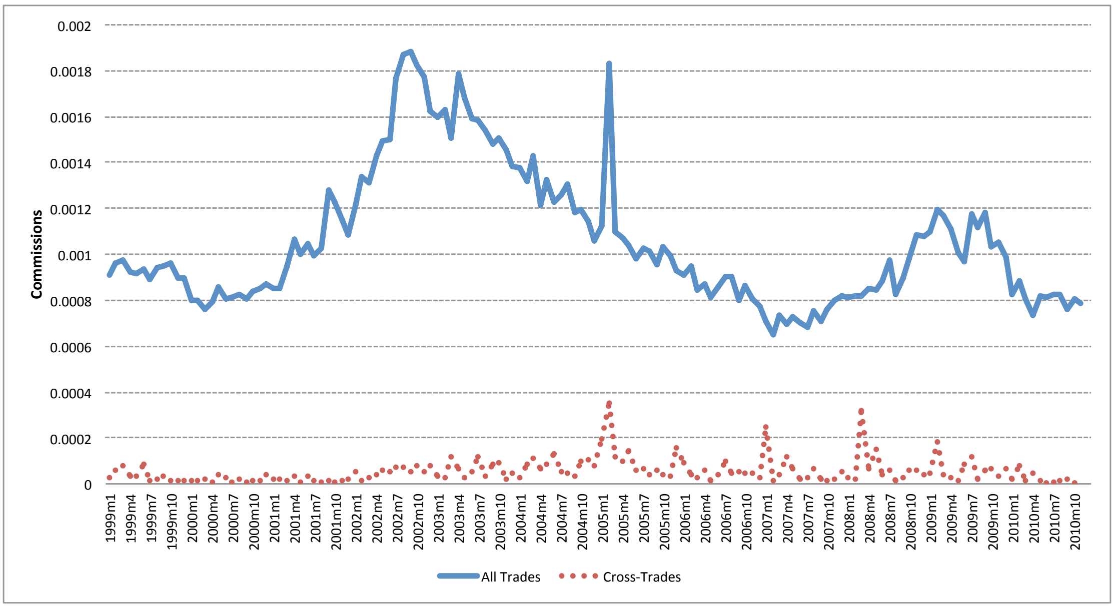
	Inflow funds		Outflow funds	
	ex. rets (1)	alpha (2)	ex. rets (3)	alpha (4)
CT	0.0841***	0.0418***	-0.0694***	-0.0386***
	(3.69)	(2.98)	(-3.70)	(-2.70)
Family Size	0.0002	0.0003***	-0.0003	-0.0001
	(1.00)	(3.23)	(-1.65)	(-0.62)
Fund Size	-0.0000***	-0.0000***	-0.0000	0.0000
	(-3.73)	(-4.09)	(-0.63)	(0.53)
Returns Dispersion	0.1117*	0.0839**	-0.0606	-0.0594**
	(1.67)	(2.49)	(-1.19)	(-2.25)
Size Dispersion	0.0000	0.0001	-0.0001	-0.0001
	(0.27)	(1.19)	(-0.71)	(-1.59)
Past Flows	-0.0052	0.0006	-0.0078	-0.0022
	(-0.61)	(0.18)	(-0.97)	(-0.47)
Past Returns	0.0761	0.0375*	0.0331	0.0057
	(0.88)	(1.66)	(0.54)	(0.34)
Constant	0.0016	-0.0026**	0.0030*	0.0005
	(0.75)	(-2.47)	(1.91)	(0.61)
Observations	36,403	36,403	35,442	35,442
R-squared	0.633	0.088	0.659	0.083

TABLE 1.12: **Lagged Cross Trading**

This table presents results for regressions of *spread* on lagged CT and controls. Each observation is obtained from the pairwise combinations of inflow funds with ouflow funds conditional of belonging to the same family, in the same month and having the same investment style. *spread* is computed as return (4-factor alpha) of inflow fund i (i.e., funds with flows in the top tercile of family f in a given month t) minus outflow fund j's return (4-factor alpha), i.e., funds with flows in the bottom tercile of family f in a given month t. Funds with flows in the intermediate tercile are dropped. CT is computed as the percentage of cross-trades in family f in month $t-1$. The independent variables are: $FamilySize$, the natural log of the lagged assets under management of the family; $\Delta Size$, the difference in the natural log of the lagged funds' i and j total assets under management; $\Delta Flows$, the difference in funds' i and j lagged flows; $\Delta Returns$, the difference in funds' i and j lagged returns; *Size Dispersion*, the size difference between the largest and the smallest fund in the family divided by the average fund size in the family; *Returns Dispersion*, the monthly cross-sectional return standard deviation inside the family. The frequency of the observations is monthly. Time fixed effects are included and errors are clustered at the time level. The sample goes from 1999 to 2010.

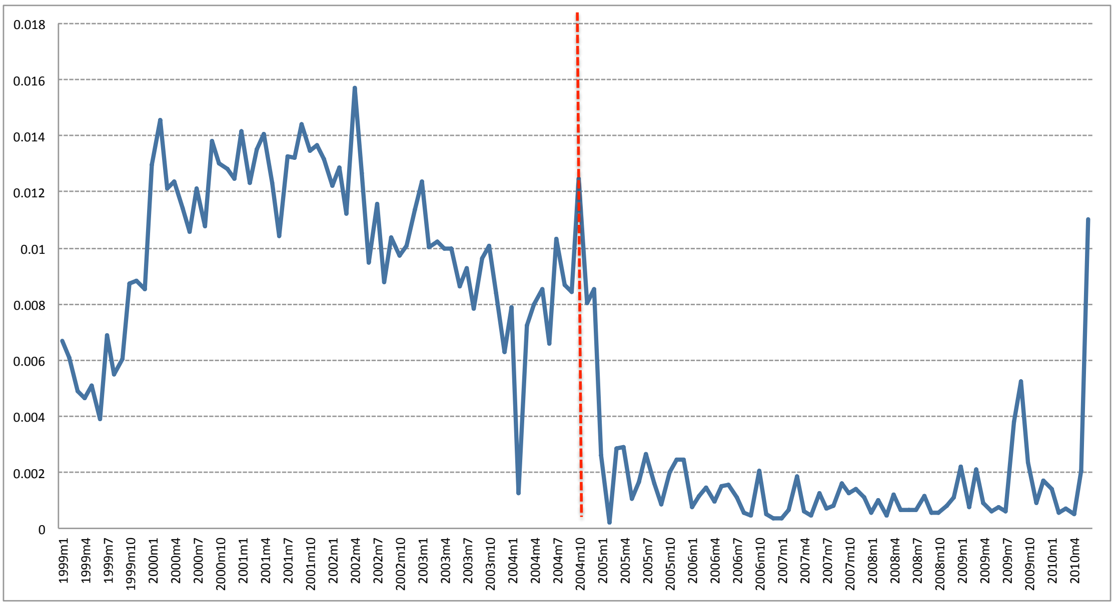
	Spread of Excess returns				Spread of 4-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged CT	0.2711***	0.1799***	0.1751***	0.1414***	0.1711***	0.0995***	0.0981***	0.0671***
	(8.81)	(5.70)	(5.56)	(4.17)	(9.66)	(5.25)	(5.24)	(3.08)
Family Size		0.0021***	0.0022***	0.0010***		0.0016***	0.0017***	0.0006***
		(9.21)	(8.72)	(3.49)		(8.05)	(8.46)	(2.80)
Δ Size		-0.0005*	-0.0006**	-0.0006**			-0.0002*	-0.0002*
		(-1.86)	(-2.01)	(-2.01)			(-1.77)	(-1.78)
Δ Returns			0.0113	0.0084			-0.0019	-0.0045
			(0.17)	(0.13)			(-0.09)	(-0.20)
Δ Flows			-0.0168**	-0.0170**			-0.0143***	-0.0144***
			(-2.04)	(-2.06)			(-2.99)	(-3.01)
Returns Dispersion				0.2874***				0.2541***
				(4.03)				(5.20)
Size Dispersion				0.0003*				0.0003**
				(1.97)				(2.27)
Constant	0.0070***	-0.0145***	-0.0144***	-0.0116***	0.0049***	-0.0114***	-0.0113***	-0.0087***
	(11.01)	(-5.98)	(-6.05)	(-4.79)	(13.43)	(-5.46)	(-5.58)	(-4.96)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	104,746	104,649	104,264	104,176	104,746	104,654	104,264	104,176
R-squared	0.120	0.126	0.124	0.125	0.057	0.062	0.063	0.065

Figure 1.1: **Trading Commissions**



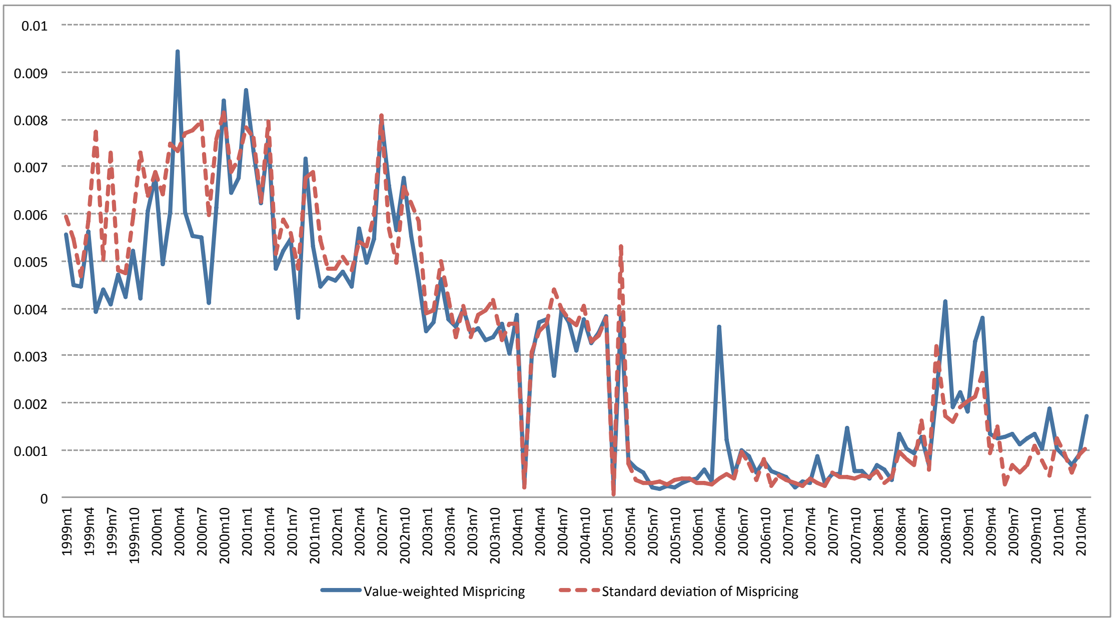
Commissions per transaction computed as the monthly average of the ratio between dollar commission paid per trade and dollar volume of the trade. Outliers (below the 1st and above the 99th percentile) are dropped. The red dashed line represents average commissions for cross-trades. Cross-trades are twin trades occurring within the same family, the same stock, day, time, volume, execution price, but opposite trade directions. The blue straight line represents average commissions for all trades recorded in Ancerno.

Figure 1.2: **Cross-trading over time**



Amount of cross-trading activity over time. Cross trading is computed for each family f in month t as the dollar amount of cross traded positions scaled by its monthly total trading volume in USD. SEC rules 38a-1 and 206(4)-7 and the amendments to rule 204-2 became effective on February 5, 2004, while the designated compliance date was October 5, 2004 (see the red vertical line). Average values are plotted for each month weighting the amount of cross-trading by the number of funds belonging to a particular family.

FIGURE 1.3: **Mispricing of Cross-Trades**



Mispricing of cross-trades over time. Mispricing is defined as the absolute deviation of a cross-trade's execution price from the volume-weighted average price of the day (VWAP). The blue straight line represents mispricing weighted by the dollar volume of the trade, the red dashed line represents the standard deviation of mispricings giving the same weight to each cross-trade. Average values are plotted for each month weighting the amount of cross-trading by the number of funds belonging to a particular family

Chapter 2

Beta Arbitrage and Hedge Fund Returns

2.1 Introduction

Historically, stocks with low sytematic risk (beta) have performed better than stocks with high sytematic risk (see Frazzini and Pedersen [25] or Baker et al. [26] for recent evidence). This result is in stark contrast with the predictions of the capital asset pricing model (CAPM) and referred to as the low beta anomaly. Theoretical and empirical research explains this violation of the CAPM by relaxing the assumption of frictionless markets. In particular, Black [27], Black [28] and Frazzini and Pedersen [25] show that in a CAPM with restricted borrowing low beta assets can have higher expected returns than high beta assets. Hong and Sraer [29] explain the flat security market line (SML) in a model featuring limited short-selling. Finally, Baker et al. [26] propose a mechanism where relative performance bechmarks can lead to overpricing (underpricing) of high (low) beta assets.

A decisive feature of hedge funds compared to many other investors is the (partial) absence of the aforementioned restrictions. Hedge funds are able to use leverage, they can short sell and they have an absolute return mandate. This paper therefore asks whether parts of the return in the hedge fund industry are generated by profiting from the regulatory or contractual restrictions imposed on other markets participants, i.e. do hedge funds take advantage of the low beta anomaly and invest in beta-arbitrage strategies?

The findings of this paper are easily summarized. First, most hedge fund styles have a significant exposure to a factor capturing the returns from beta-arbitrage strategies. More importantly, after controlling for exposure to beta-arbitrage strategies hedge funds in the aggregate and on the style level did not generate any significant abnormal returns for their investors in the period from 1994 to 2008. Second, dispersion in the exposure to beta-arbitrage strategies predicts returns in the cross-section of individual hedge fund returns. Third, the dispersion in the exposure to beta-arbitrage strategies is driven by access to leverage and risk aversion in line with theory. Overall, my results suggest that a significant part of the superior performance of hedge funds compared to other money managers is not driven by superior skill, but stems from more flexibility and less regulatory burdens.

The empirical analysis starts with an examination of hedge fund style returns. I run time-series regression of hedge fund style returns on the Fung and Hsieh [30] seven factor model augmented with a factor capturing the returns from beta-arbitrage strategies. The factor I use as a proxy for the returns from beta-arbitrage strategies is thereby throughout the paper the Betting-against-Beta factor (BAB) factor of Frazzini and Pedersen [25] which simulates the returns from a market-neutral strategy going long low beta assets and short high beta assets inside an asset class.

I find 12 out of 14 hedge fund styles have a statistically significant loading on the BAB factor in the period from 1994 to 2008 and including the BAB factor as an additional benchmark return into the performance decomposition improves the adjusted R-square of the time series regression for some styles by more than 10%. Furthermore, using the Fung and Hsieh [30] seven factor model 10 out of 14 indices exhibit significant (at the 5% level) benchmark-adjusted returns in the period from 1994 to 2008. Adding the BAB factor to the model decreases the number of hedge fund styles with significant benchmark-adjusted returns to 4. Even for the styles where the benchmark-adjusted returns stay statistically significant, the economic magnitude decreases by 50% on average.

This result is robust to the inclusion of other factors in stepwise regression framework like for example a liquidity risk factor as proposed by Sadka [31].

I also repeat the above analysis on the individual fund level. Depending on the length of the time-series between 30% and 40% of all funds in the TASS data base have a positive and significant loading on the BAB factor and the median alpha of hedge funds decreases from around 4% annually to 2.5%. Using a stepwise regression framework I find the BAB factor to the be the second most selected factor after the market factor.

After documenting a significant explanatory power in the time-series of hedge fund return the paper studies the cross-section of hedge fund returns. The paper asks whether dispersion in the loading on the beta arbitrage strategy is able to predict cross-sectional differences in hedge fund returns. I sort hedge funds at the beginning of each year into ten portfolios according to their factor loadings on the BAB factor estimated using the previous 3,4,or 5 years of data. These portfolios have a significant spread in their returns after adjusting for risk with the Fung and Hsieh [30] seven factor model. Specifically, the portfolio with the highest loading on the BAB factor (portfolio 10) outperforms the portfolio with the lowest loading on the BAB factor (portfolio 1) by 0.9% monthly. This result suggests that exposure to beta-arbitrage strategies can explain a significant amount of cross-sectional variation in hedge fund returns and including the BAB factor in a benchmark model for measuring hedge fund performance can a have a significant effect on performance rankings. This result is robust to the addition of other risk controls like the Fama and French [32] value factor, the Carhart [15] momentum factor, the Pastor and Stambaugh [33] liquidity risk factor and correcting for biases in hedge fund databases.

Finally, the paper takes a close look at long/short equity funds. Long/short equity funds constitute the largest investment style in the TASS databases and therefore are of particular interest. Furthermore, SEC regulation allows me to get quarterly snapshots of their long equity holdings which helps to gain further insight into the relation between hedge fund returns and the low beta anomaly. I find that the results documented above hold in the subsample of long/short equity and are even stronger.

Turning to the long equity holdings the first finding of the paper is that stocks held by hedge funds have on average a higher market beta than for example stocks held by mutual funds. This result runs counter to the high BAB factor exposure in the time-series regressions. The BAB factor however consists of a long position in low beta assets and a short position in high beta assets. Hence, the significant BAB exposure can be due to significant short-selling of high beta stocks. Making the simplifying assumption that most of the outstanding short-interest can be attributed to hedge fund trading (see e.g. Ben-David et al. [34]) I find that indeed the systematic risk of hedge fund short positions exceeds significantly the systematic risk of their long positions. Thus, the aggregate exposure to the BAB factor can be mainly attributed to hedge funds' short selling activity in high beta stocks.

Cross-sectional variation in the BAB factor exposure is however not only driven by variation in the short exposure to high beta stocks. I find that funds with high BAB exposure hold stocks with significantly lower systematic risk than funds with a low exposure to the BAB factor. Furthermore, results from cross-sectional regressions of hedge funds' long-side portfolio beta on hedge fund characteristics lend considerable support to the theories of Black [27] and Frazzini and Pedersen [25].

In particular, Black [27] and Frazzini and Pedersen [25] suggest that the demand for market beta should vary with the tightness of an agent's borrowing constraint. The tightness of the borrowing constraint thereby depends on agents' access to leverage and risk aversion. To proxy for a hedge fund manager's risk aversion I draw from prior literature and use as explanatory variables the existence of high-water mark provisions, share restrictions, personal capital invested in the fund and incentive fees (see e.g. Goetzmann et al. [35], Hodder and Jackwerth [36] and Panageas and Westerfield [37]). To proxy for the access to leverage I include a dummy variable equal to one when a fund reports to use leverage. Funds using leverage, with personal capital invested in the fund, a high-water mark and long redemption notice periods hold on average stocks with lower betas. To the contrary, the demand for beta positively correlates with incentive fees in line with the hypothesis that the asymmetric pay-off of incentive fees increase risk-taking.

The rest of the paper is organized as follows. Section 1 reviews related literature. Section 2 summarizes the data used in this paper. Section 3 presents empirical results and Section concludes.

2.2 Related Literature

This paper contributes to different streams of literature. First, it contributes to the literature on hedge fund performance measurement. Finding an appropriate benchmark model to measure the performance of active investors poses an ongoing challenge to academic researchers and practitioners. This holds true in particular for hedge funds. While the performance of many mutual funds is largely explained with the Fama and French [32] model augmented with the Carhart [15] factor, this is not true for hedge funds. Reasons for the weak explanatory power for hedge fund returns are manifold. Hedge funds often follow dynamic trading strategies and are able to invest across many asset classes. One way researchers have tackled this problem is through the development of asset based performance factors that are replicating the pay-offs to such strategies (see Fung and Hsieh [38], Fung and Hsieh [39]). Another way to improve the explanatory of factor models is to use conditional factor models where factor exposures are allowed to change depending on macroeconomic variables, fund performance or liquidity conditions. In a recent paper for example Patton and Ramodarai [40] propose an empirically very succesful conditional factor model for hedge funds where factor exposures are changing with high frequency movements in conditioning information. This paper belongs to the former category by proposing to use the BAB factor as an additional factor in hedge fund benchmark models. Different from for example the Fung and Hsieh [30] trend-following factors, exposure to the BAB factor not only explains hedge fund returns in the time-series of hedge fund returns, but also in the cross-section. Other recent papers finding factor exposures that predict returns in the cross-section of hedge fund return are Buraschi et al. [41], Sadka [31] and Bali et al. [42]. Buraschi et al. [41] find that exposure to correlation risk predicts return in the cross-section of hedge fund returns, Sadka [31] shows a positive relation between hedge funds' liquidity risk exposure and future returns and the results of Bali et al. [42] suggest that exposure to the default spread (inflation) predicts positively (negatively) future hedge fund returns.

Second, it relates to the literature which links cross-sectional dispersion in hedge fund returns to contractual agreements between investors and managers. Agarwal et al. [43] show that managers with more discretion and more incentives achieve higher returns for their investors. Aragon [44] argues that hedge funds with share restrictions in place achieve higher returns for their investors because they invest in more illiquid securities. My results suggest that these effects are partially due to the effect that e.g. higher discretion in the form of longer redemption notice periods leads to a stronger tilt towards a beta arbitrage strategy.

Third, it contributes to the asset pricing literature by finding support for the empirical predictions of asset pricing models with borrowing constraints (e.g. Black (1972) and Frazzini and Pedersen [25]).

2.3 Data and Methodology

2.3.1 Hedge Fund Data

2.3.1.1 Individual Fund Data

The paper uses return data (net-of-fees) reported in the TASS database between 1994 and 2008. Before 1994 TASS only reports data on "live" hedge funds. To mitigate survivorship bias the study focuses therefore on the post 1994 period when the "Graveyard" database containing dead hedge funds became available. Besides restricting the sample period I impose several other filters on the data. First, I only keep funds with a monthly reporting frequency. Second, I only keep funds with at least 18 observations as I need a sufficient number of observations to run the factor modeIs. Third, I only keep funds reporting their returns in USD. After imposing these filters I am left with 7355 hedge funds. Table 1 shows the summary statistics for these funds.

Panel A summarizes the data by year. Column 1 shows the number of funds in the sample. This number is steadily increasing from around 1000 in 1994 to around 5000 in 2007. In 2008 the number of hedge funds in the sample decreases the first time due to the financial crisis. Average monthly returns are reported in column 2. The year 2008 was by far the worst year for the industry measured by average returns or median returns (column 7). Furthermore the standard deviation of hedge fund returns significantly increased during that period.
Panel B shows the same statistics as Panel A by investment style. Each hedge fund in TASS reports to follow one of 11 investment styles: Long/Short Equity Hedge, Event Driven, Multi-Strategy, Equity Market Neutral, Convertible Arbitrage, Fixed Income Arbitrage, Global Macro, Dedicated Short Bias, Emerging Markets or Managed Futures. Long/Short Equity Hedge constitute the largest investment style in the hedge fund universe, whereas Dedicated Short Bias is by far the smallest investment style. Although these classifications offer some insight into a fund's investments, there is still a lot of heterogeneity inside the different styles. An event driven fund for example can be a pure merger arbitrageur or a pure distressed securities investor.

Panel C reports cross-sectional statistics for different fund characteristics. The distribution of assets under management (AUM) is highly skewed with a mean of USD 121 million and a median of USD 32 million. The median of the management fee and incentive fees are 1.5% and 20%. Panel C also reports other variables of interest which will be defined later. All the statistics reported in Panel C are however very closely to the ones reported in other studies (see Bali et al. [42] or Agarwal et al. [43]).

2.3.1.2 Hedge Fund Index Data

I obtain hedge fund index data from TASS. An alternative to using the provided indices by TASS is to construct the indices from the individual fund data. The TASS indices however offer a finer style classification and are widely used by practitioners. The TASS indices are value-weighted and funds have to meet several criteria like e.g. a certain size to be included in the index calculation[1]. Due to the value-weighting the indices are well suited to gain insight into the hedge fund industry.

2.3.1.3 13F Data

For the holdings data I extract quarterly 13F filings which have to be submitted to the SEC on a quarterly frequency by investment advisors with investment discretion in excess of USD 100 million at the end of the previous year. A drawback of the 13F data is that 13F filers do not have to disclose their full portfolios but only holdings in qualified securities as specified by the SEC and holdings which exceed certain size thresholds. Important for the analysis of hedge funds is the non-disclosure of short positions. Hence, in the holdings analysis the paper looks only at the long positions and inside the long holdings only at the equity positions.
To identify hedge funds among the 13F institutions I use first a proprietary list of hedge funds from Thomson-Reuters.[2] Afterwards I match the 13F institutions manually to the TASS database to obtain fund characteristics. As the 13F filing are reported on the management company level, which often includes several hedge funds, I aggregate the characteristics at the management company level by computing an AUM weighted average of each characteristic. After the manual match the sample includes 650 hedge funds belonging to 250 management companies. Finally, I focus on Long/Short Equity Funds, which leaves me with 125 management companies.

Table 2 shows the summary statistics for the smaller sample of hedge fund management companies matched with TASS. I focus on data after 1998 to have a sufficient number of observations in the cross section. Row 1 shows the market beta of hedge funds' long equity holdings. The other rows report assets under management (AUM) from TASS, the size of the long equity portfolio from 13F, the incentive fee in percent, the management fee in percent, the redemption notice period in days, the lockup period in month, and a dummy which indicates whether a hedge fund is using leverage.

[1] More details on the index construction can be obtained from www.hedgeindex.com
[2] I am grateful to Francesco Franzoni for providing this list

The most obvious difference between Table 1 Panel C and Table 2 is the average size of the funds. Funds in Table 2 are significantly larger due to two facts. First, the statistics are reported on the level of the management company. Second, as mentioned above hedge funds only have to report to the SEC when their AUM exceeds USD 100 million.

2.3.2 Hedge Fund Return Decomposition

The literature on portfolio performance evaluation aims to separate the part of a portfolio's return which is due to the genuine skill of the manager (alpha) from the part which can be explained through exposures to passive benchmarks. It is thereby irrelevant whether the passive benchmark captures an economic risk factor or whether the passive benchmarks capture some source of mispricing. To decompose the performance a factor model of the form

$$r_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_i^k F_t^k + \epsilon_t^i$$

is used, where $r_{i,t}$ is the return of fund i at time t, $\alpha_{i,t}$ is the regression intercept of the multivariate regression of fund returns on K different benchmark returns F_t^k and $beta_i^k$ are the slope coefficients.

This paper uses for most of the analysis the Fung and Hsieh [30] seven factor model as a benchmark model. The seven factors are the excess return on the market (MKTRF) and the small minus big factor (SMB) of Fama and French [32]; the excess returns on portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the change in the constant maturity yield of the U.S. 10-year Treasury bond over the 3-month T-bill (BD10RET); and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond(BAAMTSY).

In order to test whether hedge funds are loading on a strategy taking advantage of the low beta anomaly I augment the Fung and Hsieh [30] model with the betting against beta factor of Frazzini and Pedersen [25] [3]. The BAB factor is a long short portfolio taking a leveraged long position in low beta assets and a deleveraged short position high beta assets. The levels of leverage for the long and short side are thereby chosen in such a way that the resulting long-short portfolio is beta neutral. Frazzini and Pedersen [25] construct BAB factors for a number of different asset classes including US equities, international equities, currencies, commodities, CDS, treasuries, corporate bonds, country bonds and equity indices. Due to the discretion of their trading behavior many hedge funds are able to invest in any asset class. Instead of trying to pick a specific BAB factor I therefore simply take the composite BAB factor provided by Frazzini and Pedersen [25].

While the factors of Fung and Hsieh [30] are the most commonly used ones, there are a number of other benchmarks hedge funds are exposed to. First, long/short equity funds often exhibit significant exposures to the value factor (hml) of Fama and French [32] and the momentum factor (umd) of Carhart [15]. Second, the recent literature stresses the importance of liquidity risk to understand hedge fund returns. Sadka [31] for example finds market liquidity risk to be an important explanatory variable in the time-series and cross-section of hedge fund returns. Therefore I use the liquidity risk factor of Pastor and Stambaugh [33] in my analysis. As a second liquidity risk factor I use the leverage mimicking portfolio (LMP) of Adrian et al. [45]. Adrian et al. [45] create a factor that mimicks the leverage of financial intermediaries and show that this factor has very strong explanatory in the cross-section of assets [4]. In particular, their results suggest that their factor is able to explain the cross-section of returns of beta sorted portfolios.

Table 3 shows summary statistics for the different factors. The highest average returns during the sample period generated the LMP factor with 0.88% per month. The LMP factor is closely followed by the momentum factor (umd) with monthly returns of 0.87%

[3]The authors made their BAB factors available at http://people.stern.nyu.edu/lpederse/.

[4]Adrian et al. [45] compute first quarterly shocks to the leverage of the financial intermediary sector and in the second step they project the leverage shocks on the 6 book-to-market and size sorted portfolios of Fama and French [32] and the momentum factor of Carhart [15] to get a traded factor. The estimated parameters of the projection are reported in Adrian et al. [45] and are used in this paper for the computation of the LMP factor

per month. On a risk-adjusted basis however the picture changes. The standard deviation of the LMP factor and the momentum strategy are both more than three times the standard deviation of the BAB factor. Hence, with a sharpe ratio higher than one during the period from 1994 to 2008 the BAB strategy is significantly more attractive than the returns of other mimicking portfolios.

2.4 Beta Arbitrage and Hedge Fund Returns

2.4.1 Investment style exposure

I start the empirical analysis with an examination of different hedge fund investment styles to understand whether hedge funds in the aggregate generate parts of their returns through beta arbitrage strategies. In the following analysis I use the aforementioned factor model to decompose hedge fund returns into skill and exposures to different passive benchmarks.

Panel A of Table 4 shows results using the Fung and Hsieh [30] model. In order to interpret the intercepts of the time-series regressions as alphas I follow Sadka [31] and replace the term spread with the Barclay's 7-10 year treasury index minus the short-term rate and changes in the credit spread with the Barclay's corporate bond Baa index minus the 7-10 year treasury index. Column 1 of Panel A finds risk-adjusted returns in the hedge fund industry of 0.3% per month or 4% annually between 1994 and 2008. The highest risk-adjusted returns were generated by funds following Global Macro strategies. The Global Macro index generated risk-adjusted returns of 0.6% monthly or 7.5% annually over the period from 1994 to 2008. Most of the investment styles are not market neutral, but have an economically and statically significant exposure to market risk. Other important risk factors are the size factor (SMB) of Fama and French [32], the credit spread and the term spread.

In Panel B of Table 4 the BAB factor is added as a regressor. The results suggest that except for the Dedicated Short Bias and the Equity Market Neutral strategy the BAB factor is significantly correlated with hedge fund style returns. The explanatory power of the BAB factor is thereby particularly strong for Convertible Arbitrage(CA) funds and Fixed Income Arbitrage (FIA) funds. The time-series R^2 increases from 0.29 to 0.4 for CA funds and from 0.32 to 0.47 for the FIA funds. Controlling for exposure to the BAB factor Panel B of Table 4 shows that the only hedge fund styles delivering significant risk-adjusted returns during the period 1994 to 2008 were Equity Market Neutral, Event Driven and the subindex Distressed Securities. This compares to 10 indices with significant risk-adjusted returns using the Fung and Hsieh [30] seven factor model. The risk-adjusted returns for Fixed-Income Arbitrage funds even turn significantly negative.

The significant explanatory power of the BAB factor in the time-series of hedge fund returns can be due to other omitted factors in the regressions. Important candidates for such omitted factors are liquidity risk factors and a value factor. Frazzini and Pedersen [25] show theoretically that the returns of the BAB factor are strongly correlated with funding liquidity risk. Brunnermeier and Pedersen [46] furthermore argue that there exists a close relationship between funding liquidity risk and market liquidity risk. In their model the unwinding of trades from arbitrageurs facing funding liquidity shocks can lead to a deterioration of market liquidity. In line with this idea Sadka [31] and Teo [47] find a strong correlation between market liquidity risk and hedge fund returns. Thus, the correlation between the BAB factor and hedge fund returns is potentially due to the correlation with market liquidity risk. Franzoni [48] finds a strong decrease in the market beta of value stocks in recent years. Hence, the significant loading on the BAB factor could also be explained by a value tilt in hedge fund portfolios.

In order to test whether hedge funds' exposure towards beta arbitrage strategies is a dominant factor after considering a number of other potential benchmark strategies I employ the stepwise regression framework used by Agarwal and Naik [49]. In a stepwise regression variables are added or deleted as explanatory variables depending on the F-Value which eventually leaves a small set of variables maximizing the in-sample fit of the regression. A drawback of stepwise regressions is in-sample overfitting and a breakdown of standard statistical inference. Agarwal and Naik [49] however empirically find a good out-of-sample performance of the extracted factors and the authors suggest that the benefits of the stepwise regression approach outweigh the costs in the case of hedge fund performance attribution.

I run the stepwise regressions using the 12 benchmark returns from Table 3 and show the results graphically in Figure 1. Figure 1 shows for every TASS index return its average annual excess return and the contribution of the exposure to a beta arbitrage strategy to this performance. If the stepwise regression did not extract the BAB factor as a dominant return source, the contribution to the performance of the TASS index return is zero. If the stepwise regression did extract the BAB factor as a dominant factor, the contribution is equal to the factor exposure times the average return of the BAB factor. Figure 1 suggests the BAB factor contributes significantly to the returns of 10 out of the 14 indices. For the broad hedge fund index, the long/short equity index and several event driven strategies the economic contribution of the BAB factor is around 20%. Especially high is the economic contribution to the strategies convertible arbitrage, fixed income and multi-strategy. For some of these strategies the economic contribution even exceeds 100%.

Overall the results from this section suggest that significant parts of the hedge fund industry are loading on a beta arbitrage strategy and controlling for this exposure has a significant impact on estimated alphas. Specifically, using the Fung and Hsieh [30] seven factor model augmented with the BAB factor only 4 out of 14 hedge fund styles delivered statistically significant risk-adjusted returns in the period from 1994 to 2008. To the contrary, using only the Fung and Hsieh [30] seven factor model 10 out of 14 hedge fund styles delivered positive and significant risk-adjusted returns.

2.4.2 The Cross Section of Individual Hedge Funds

The previous section examines hedge fund returns on the index level. In this section I first study the number of individual hedge funds having a positive and significant loading on the BAB factor. Second, I analyze whether cross-sectional dispersion in the loading on the BAB factor can explain differences in hedge fund expected returns. If the loading on the BAB factor can explain differences in hedge fund expected returns, augmenting the Fung and Hsieh [30] model with the BAB factor can have important consequences for hedge fund performance rankings with a significant impact on manager selection.

2.4.2.1 Individual Hedge Funds' Exposure to Beta Arbitrage Strategies

I decompose the returns of all hedge funds in the dataset using the Fung and Hsieh [30] model augmented with the BAB factor of Frazzini and Pedersen [25]. Individual hedge funds often have very short time series and a recent paper by Bollen [50] stresses the problems of making inferences with such short histories. In particular, the paper points out the problem of finding spurious results using short return histories. To reduce these problems I report results with different required minimum return histories ranging from 3 years to 10 years.

Depending on the minimum number of required observations Panel A Table 5 finds that between 30% and 40% of all funds have a significant exposure. In contrast, the number of funds having a negative and significant loading on the BAB factor is very small. Panel B looks at different investment styles requiring a fund to have a minimum of 36 time series observations to be included. Among the investment styles with the largest fraction of positive and significant loadings on the BAB factor are convertible arbitrage and event driven funds.

In line with the results from the previous section Table 5 also shows that the BAB factor has a significant effect on risk-adjusted returns. Using the Fung and Hsieh [30] seven factor model the median hedge fund alpha is around 4% annually. Adding the BAB factor decreases annual alpha by an economically significant magnitude of 1.5% annually. Among the different investment styles exposure to the BAB factor has a strong impact on risk-adjusted performance in particular for managed futures, convertible arbitrage and emerging markets. The annualized alpha for managed futures decreases from 6.1% to 3.7% and for emerging market funds from 7.1% to 1.7%.

Finally, similar to the analysis on the index level I also employ the stepwise regression framework to the individual funds. Using the 12 benchmark returns from Table 2 I run a stepwise regression for every hedge fund with a return history of at least 36 month and Figure 2 shows the 5 most often selected benchmark returns. For every benchmark the first bar shows the percentage of funds choosing the benchmark and the second bar shows the percentage of funds having a positive exposure to the benchmark return. The market factor is the most important benchmark and is selected by more than 50% of all funds. The Betting-against-Beta factor is the second most selected factor and is selected for more than 25% of all funds. The BAB factor is followed by the Carhart [15] momentum factor and the Fama and French [32] size and value factors. Given a certain benchmark return is selected a fund's exposure is mostly positive. An exception is the value factor where the number of funds having a significant negative exposure is nearly equal to the number of funds having a positive exposure.

The results from this section broadly confirm the results from the previous section. A large fraction of hedge funds load significantly on a long low beta assets and short high beta assets portfolio and including such Betting-against-Beta (BAB) factors into a benchmark model to decompose hedge fund returns has strong effects on hedge fund risk-adjusted returns. Whereas the Fung and Hsieh [30] model suggests that the median hedge fund delivered risk-adjusted performance of over 4% to its investor in the past, a model augmented with a BAB factor decreases this number by more than 1% annually.

The results also suggest heterogeneity in the loading on beta arbitrage strategies proxied by the BAB factor as not all hedge funds significantly load on the factor. In the next section I examine whether this heterogeneity is able to explain differences in hedge fund expected returns.

2.4.2.2 Beta Arbitrage and the cross-section of hedge fund returns

Do cross-sectional differences in the exposure to the beta-arbitrage strategy lead to statistically and economically significant dispersion in excess returns after controlling for exposure to other benchmark strategies? The Fung and Hsieh [30] factors have a good explanatory power in the time-series, but dispersion in the exposure to the Fung and Hsieh [30] factors does not create any statistically and economically meaningful dispersion in the cross-section of hedge fund returns (Sadka [31], Bali et al. [42]). Hence, a significant explanatory of the BAB factor in the time-series does not necessarily imply a significant explanatory in the cross-section.

To answer the question whether differences in the exposure to the BAB factor generates differences in the cross-section of hedge fund returns I sort hedge funds into ten portfolios according to their loading on the BAB factor and study the equally-weighted post-ranking returns of the portfolios. Hedge fund factor betas can vary through time as a function of macroeconomic state variable or fund specific characteristics (see Patton and Ramodarai [40]). In order to take into account potential time-variation in factor loadings I use rolling beta estimates. While rolling regressions capture time-variation in the factor loadings they are also likely to be noisy due short estimation windows. Following the previous section I report post-ranking returns for different estimation windows.

In January of each year beginning in 1999 I sort all hedge funds into 10 portfolios according to their loading on the BAB factor. The loading on the BAB factor is computed with a multivariate regression of a hedge fund's monthly excess return on the Fung and Hsieh [30] factors and the BAB factor using different estimation windows up to 60 months. Afterwards the funds are sorted into ten equally weighted portfolios according to their BAB loading. The post-formation returns of these portfolios during the next 12 month are linked across years to obtain for each portfolio a 10 year return time series. The performance of these portfolios is then evaluated against the Fung and Hsieh [30] seven factor model.

Table 6 suggests that variation in the loadings on the BAB factor leads to significant dispersion in hedge fund returns. Portfolio 1 reports the risk-adjusted returns and factor loadings of hedge funds with a low loading on the BAB factor, portfolio 10 for funds with a very high loading on the BAB factor and the last column shows the spread between the two extreme portfolios. Funds in portfolio 1 generated insignificant risk-adjusted returns in the period from 1999 to 2008. In contrast funds in portfolio 10 have a high loading on the BAB factor and with an average monthly alpha between 0.9% and 1% they significantly outperformed the funds in portfolio 1. Besides a significant spread in the alphas of these portfolios Table 6 also reports significant differences in the factor loadings of these two portfolios. Funds in portfolio 1 have on average a significantly higher loading on the market factor. This suggests that these funds are not only investing in high beta securities, but their bets are also more directional. Furthermore funds in portfolio 1 also have higher loadings on the smb factor and the credit spread. Small cap securities have higher betas and therefore a higher loading on the smb factor is intuitive. Frazzini and Pedersen [25] show in their model that the BAB factor is sensitive to funding liquidity shocks. Hence, when credit spreads are increasing funds with a high BAB exposure experience lower returns.

The results stay economically as well as statistically the same when the required number of observations required for inclusion is increased. Indeed, the results even become stronger with the required number of observations. Exposure to beta arbitrage strategies seem to be an important systematic driver of hedge fund performance and inclusion of the BAB factor in a benchmark model can have a significant effect on hedge fund performance rankings.

2.4.2.3 Robustness

Hedge fund data are susceptible to many biases due to the lack of regulation among hedge funds. Inclusion in hedge fund databases is voluntary which results in a self selection bias. In particular there is an incubation bias and a backfill bias. Funds often rely on internal funding before they try to raise capital from outside investors. Funds with successful track records list in a hedge fund databases while the unsuccessful funds do not. This results in an incubation bias. On the other hand funds often backfill their data, i.e. the database includes data prior to the listing date. These backfilled returns tend to be higher than the non-backfilled returns. To control for these biases I repeat the portfolio sorts dropping the first 12 return observations of every fund. Panel A of Table 7 shows that this does not change the results. Risk-adjusted returns are still increasing monotonically from the first to the tenth decile and the 10-1 spread is statistically significant albeit economically smaller.

Besides backfilling their data hedge funds often hold illiquid securities or deliberately smooth their returns which can lead to significant serial correlation of hedge fund returns. To control for serial correlation I unsmooth hedge fund returns using the model of

Getmansky et al. [51]. Similar to the effect of correcting for backfill and incubation bias Panel B of Table 7 shows a decrease in the economic magnitude of the 10-1 spread. The magnitude is however still economically meaningful and statistically significant.

The results reported in this paper could be due to the specific risk model used. Therefore, I use different models to adjust hedge fund returns for exposures to risk. As mentioned earlier Frazzini and Pedersen [25] point out the close relation between the BAB factor and liquidity risk. The Fung and Hsieh [30] seven factor model includes the change in the credit spread, a measure for funding liquidity conditions. Hence in the portfolio sorts the paper already controls for exposure to funding liquidity risk. There is however no control for market liquidity risk. To control for market liquidity risk I repeat the portfolio sorts and augment the seven factor model with the traded market liquidity risk factor by Pastor and Stambaugh [33]. Panel C of Table 7 suggests that exposure to the liquidity risk factor does not explain the spread in risk-adjusted return between the first and the tenth portfolio. Finally, Panel D of Table 7 presents results using the Fama and French [32] model augmented with the Carhart [15] momentum factor. Again, the results stay economically meaningful and statistically significant.

2.4.3 A close look at long-short equity funds

In this section I take a close look at long/short equity funds. First, long/short equity funds are the most important hedge fund style with roughly 40% of funds falling into this style category. Second, many long/short equity funds have to file regularly with the SEC. This gives me the opportunity to have a snapshot on their holdings and allows me to test theories explaining the low-beta anomaly.

2.4.3.1 Beta Arbitrage and the performance of long/short equity funds

I repeat the analysis from Table 6 keeping only long/short equity funds. I focus on the results using a 36 month estimation period for the pre-ranking betas. The results in Panel A of Table 8 suggest that dispersion in the loading on the BAB factor leads to a stronger dispersion in returns for long/short equity funds than for the whole universe of funds. Funds with a high loading on the BAB factor outperform funds with a low loading by 1.2% monthly between 1999 and 2008. Correcting for potential biases in hedge fund databases and using different models for the risk-adjustement does not change these conclusions as shown in Panels B to D of Table 8 . Using the Fama and French [32] three factor model augmented with the Carhart [15] momentum factor leads however to a significant decrease in the 10-1 spread. Franzoni [48] empirically analyses the time-series evolution of the market exposure of value stocks and documents a steady decrease since around 1940. Hence, some fraction of the dispersion in risk-adjusted returns between the first and tenth portfolio can be attributed to dispersion in the value factor. Unreported results show that funds in the first decile indeed load significantly negative on the value factor whereas funds in the 10th decile load significantly positive on the value factor. Exposure to the value factor is however not able to explain the 10-1 spread completely. The spread stays statistically and economically significant.

2.4.3.2 Do hedge funds hold low beta securities?

In the previous analysis I assume the loading on the BAB factor is a valid proxy for the systematic risk of the securities a hedge fund holds. In this section I provide direct evidence for this conjecture using mandatory hedge fund disclosures from the 13F filings. Table 2 reports summary statistics of the market beta of hedge fund long equity holdings. The mean and median are around 1.1. Contrary to the results from the factor model regression this implies that hedge funds are actually buying more market risk than other market participants. Frazzini and Pedersen [25] for example report a mean market beta for mutual funds of 1.06. Hedge funds tilt their portfolios stronger towards small cap securities which are usually more sensitive to aggregate market movements. Hence, the higher market beta in the aggregate is not surprising.

What drives then the high BAB exposure in the factor model regressions? One explanations could come from the short side. While hedge funds are maybe not long low beta securities, they are short high beta securities. Data on short positions of individual hedge funds is not available. However, one can analyze short interest data reported by the exchanges and make the assumption that short selling transactions are mainly driven by hedge fund trading. Supporting evidence for this simplifying assumption can be found in Ben-David et al. [34]. Figure 3 plots the value weighted beta of hedge fund long equity holdings and the value weighted beta of short interest. The beta of short positions is significantly higher than the beta of long positions. Specifically, the mean beta of short positions is 1.21 compared to 1.13 for the long holdings and the difference is statistically different from zero (the t-statistic is 7.3). Thus, on an aggregate level the significant loading on the BAB factor seems to be due to the short side, i.e. hedge funds are shorting high beta securities.

Next, I take a look into the cross-section. If variation in the exposure to the BAB exposure is solely driven by the short side I do not expect to see any differences in the long side across beta sorted hedge funds. In Table 9 I use the portfolio assignments from the previous section (where the results are reported in Table 8) and compare funds' portfolio betas in the different deciles. The betas are monotonically declining from the first to the tenth portfolio and the difference in betas is highly statistically significant. Thus, hedge funds with a higher factor loading on the BAB factor seem to invest in stocks with lower betas.

2.4.3.3 Which hedge funds hold low beta securities?

Frazzini and Pedersen [25] suggest that more risk averse investors and investors having a better access to leverage tilt their portfolio stronger towards low beta securities. In particular they show theoretically that the tangency portfolio in a borrowing restricted CAPM has a beta smaller than one. In this section I explore the effects of risk aversion and access to leverage on the beta of the long side of my sample of hedge funds.

I start with the effects of leverage. In Table 10 column 1 I regress a hedge fund's unlevered long-side portfolio beta on a dummy variable equal to one if the fund uses leverage. The coefficient is negative and significant. This result is consistent with the theory that funds having access to leverage are tilting their portfolio weights stronger towards low beta assets. The coefficient of -0.03 is economically however small which can have different reasons. First, I use a dummy variable for leverage. The cross-sectional variation among hedge fund leverage can be large with higher leverage funds stronger tilting towards low beta assets. Using the dummy variable approach only captures the mean change in long-side portfolio beta for all funds using leverage. In unreported results I use a fund's average leverage during its existence as independent variable. The results stay nearly unchanged and I stick to the leverage dummy in the rest of the paper. Second, leverage can be correlated with risk aversion. In a CAPM world the observation of an investor using more leverage is an indicator of a lower risk aversion. Leverage therefore is only a raw proxy for access to funding liquidity as it does not measure potential leverage but rather realized leverage. Overall, using reported leverage by hedge funds probably understates the correlation between access to funding liquidity and long-side beta.

Whether a borrowing constraint binds depends not only on access to leverage, but also on an agent's risk aversion. For any given level of potential leverage, the borrowing constraint is more likely to bind for the less risk averse investor. To study the effect of risk aversion on hedge fund's long-side beta I draw from a large literature suggesting different variables that have an effect on the effective risk aversion. Goetzmann et al. [35] and Panageas and Westerfield [37] show that incentive fees encourage risk taking, i.e. they decrease the risk aversion. The results in Table 10 column 2 show that the incentive fee has a positive impact on the preference for beta. While incentive fees decrease risk aversion, a high-water mark provision or personal capital invested can increase risk aversion. When a fund manager for example has personal capital invested in the fund he participates in the gains and losses of the fund symmetrically which makes him more risk averse. Column 3 of Table 10 shows that the presence of a personal capital stake as well as a high-water mark provision has a significant and negative impact on the beta of the long holdings. Another channel which can potentially influence the risk aversion is the flow performance relationship. Ding et al. [52] show that the flow performance relationship of hedge funds is convex in the absence of share restrictions and concave in the case of share restrictions. Hence in the absence of share restrictions hedge funds have a stronger incentive to take on higher risks in order to attract more flows. In column 4 of Table 10 I therefore add the lock-up periods as well as the redemption notice period to the model. The results suggest that stronger share restrictions i.e. longer lock-up period as well as longer redemption notice periods lead to a lower demand for beta.

Finally, in the last column I add macroeconomic variables to the regression. In particular I add the VIX index as a proxy of aggregate risk aversion and the TED spread as a proxy for funding liquidity. When risk aversion as proxied by the VIX index is increasing, hedge funds are moving from high beta to low beta securities. To the contrary, when the TED spread is increasing hedge funds are moving towards high beta securities. Overall the results in this section are broadly in line with the model of Frazzini and Pedersen [25].

2.4.3.4 Hedge fund characteristics and stock preferences

For completeness, this section studies which factors drive hedge funds' demand for other stock characteristics. This is important to rule out other explanations for my results. I therefore use the last specification from Table 10 and use as the dependent variable other stock characteristics. In particular, I focus on total volatility, the book-to-market ratio and momentum. For every hedge fund I thereby compute the value-weighted average of these characteristics using the reported long-equity holdings.
Column 1 of Table 11 shows for comparison again the results when the portfolio beta is the dependent variable. In column 2 of Table 11 I use total volatility instead. It is notoriously hard to disentangle systematic volatility from idiosyncratic volatility. Often stocks with high systematic volatility also have high idiosyncratic volatility. It is however interesting to observe that leverage does not have a significant effect on a hedge fund's preference for total volatility of a stock. One can argue that the negative effect of leverage on the preference for beta is due to e.g. portfolio margining. Until 2007 margin requirements were computed on a stock-by-stock basis and since 2007 portfolio margining was introduced where required margins are based on the value at risk of the total portfolio. At least before before 2007 to minimize the required margin and lever up as much as possible a hedge fund should choose therefore stocks with low total volatility. According to this argument the relation between leverage and total volatility should be stronger than the relation between beta and leverage. Table 11 however suggests a weaker relation between leverage and total volatility.

Column 3 of Table 11 uses the book-to-market ratio as the dependent variable. The paper already pointed out, that there is a high correlation between value investing and low beta investing due to the steady decrease in the systematic risk of value stocks documented by Franzoni [48]. Are hedge funds with a strong value tilt also hedge funds with a low beta tilt? Column 3 of Table 11 suggests that there are differences. A hedge fund's value tilt does not depend on its use of leverage and the value tilt increases with the incentive fee whereas the low beta tilt decreases with the incentive fee. Thus, hedge funds with a low beta tilt are not necessary value investors.

The last column of Table 11 shows results with momentum as the dependent variable.

2.5 Conclusion

This paper documents that a factor capturing the return from beta-arbitrage strategies has significant explanatory power in the time-series and cross section of hedge fund returns. It studies furthermore how the exposure towards this factor is related to the contractual agreements between hedge fund managers and investors.

The results of this paper have several implications. First, they provide empirical support for the model of Frazzini and Pedersen [25]. Second, the results suggest that some of the high risk-adjusted returns in the hedge fund industry reported in earlier studies can be attributed to strategies exploiting the low-beta anomaly. Third, the results are important from an asset allocation perspective. As some hedge funds have a strong tilt towards low beta assets, investments into these funds can help institutional investors to achieve exposure to the attractive risk return trade-off of these assets.

TABLE 2.1: **Summary Statistics**

There are a total of 7355 hedge funds reporing monthly returns and characteristics to TASS for the years 1994 to 2008. Panel A shows for each year the number of funds in the database (N) and summary statistics for monthly returns. Mean, Minimum, 1th Pct., 25th Pct., Median, 75th Pct., 99th Pct. and Std. Dev. are time-series averages of cross-sectional statistics. Panel B shows the same statistics for the different investment styles. Panel C report cross-sectional statistics for different hedge fund characteristics.

	N	Mean	Minimum	1th Pct.	25th Pct.	Median	75th Pct.	99th Pct.	Std. Dev.
Panel A: All funds, per year									
1994	927	-0.0	-32.0	-12.5	-2.0	-0.0	1.8	14.1	4.7
1995	1209	1.3	-29.1	-10.5	-0.6	1.0	2.7	15.9	5.4
1996	1504	1.4	-47.8	-11.3	-0.4	1.2	3.0	17.2	5.5
1997	1759	1.4	-39.1	-13.1	-0.5	1.3	3.3	16.6	5.3
1998	2035	0.4	-56.5	-19.2	-1.8	0.5	2.7	17.1	6.6
1999	2334	2.0	-42.3	-12.6	-0.3	1.4	3.7	21.5	5.9
2000	2637	0.9	-48.1	-16.3	-1.3	0.8	2.8	20.1	6.2
2001	2977	0.5	-41.7	-13.3	-0.8	0.6	1.8	14.4	4.8
2002	3363	0.3	-46.3	-10.5	-0.8	0.3	1.3	12.0	4.7
2003	3845	1.3	-45.1	-6.4	0.1	0.9	2.0	12.2	3.5
2004	4388	0.7	-43.1	-6.1	-0.2	0.6	1.4	8.6	2.8
2005	4913	0.8	-47.2	-6.0	-0.2	0.6	1.6	8.8	2.8
2006	5151	0.9	-46.6	-6.0	-0.0	0.8	1.7	9.3	3.1
2007	5015	0.8	-39.0	-6.9	-0.2	0.7	1.7	10.0	3.7
2008	4391	-1.4	-67.4	-17.1	-3.0	-1.1	0.8	10.9	5.3
Panel B: Full sample statistics, by investment style									
Convertible Arbitrage	227	0.5	-9.1	-7.9	-0.3	0.5	1.3	7.8	2.5
Dedicated Short Bias	46	0.3	-8.7	-8.7	-2.2	0.5	2.9	8.9	4.5
Emerging Markets	607	1.0	-18.2	-13.1	-2.0	0.7	3.6	18.7	5.9
Equity Market Neutral	482	0.8	-11.3	-8.5	-0.5	0.7	2.0	10.6	3.4
Event Driven	629	0.8	-14.4	-7.2	-0.3	0.7	1.8	10.9	3.2
Fixed Income Arbitrage	316	0.6	-11.3	-9.6	-0.2	0.7	1.5	10.5	3.1
Global Macro	430	0.7	-15.9	-13.7	-1.5	0.6	2.7	16.5	4.9
Long/Short Equity Hedge	2781	1.0	-27.4	-11.1	-1.2	0.9	3.2	14.8	4.8
Managed Futures	731	0.9	-27.8	-15.4	-1.8	0.7	3.4	18.1	6.1
Multi-Strategy	892	0.8	-16.1	-9.4	-0.3	0.8	1.9	10.8	3.4
Panel C: Cross-sectional Statistics									
						N	Mean	Median	Std. Dev.
AUM (in million USD)						7355	121.7	32.9	377.6
Incentive Fee (in %)						7355	15.5	20.0	7.6
Management Fee (in %)						7355	1.5	1.5	0.8
Redemption notice period (in days)						7355	36.4	30.0	29.8
Lock-up period (in month)						7355	3.1	0.0	6.2
Highwater-Mark						7355	0.6	1.0	0.5
Personal Capital						7355	0.3	0.0	0.5
Minimum Investment (in million USD)						7355	1.2	0.1	14.3
Leverage						7355	0.57	1	0.49
Age						7355	80.8	44.0	50.7

Table 2.2: **Hedge Funds' Holdings Data**

This table shows summary statistics for the Long-Equity Holdings for 125 Long/Short Equity Hedge Funds obtained through a merge between the TASS database and SEC 13F filings. All statistics are estimated by pooling time-series and cross-sectional observations.

	Mean	25th Pct.	Median	75 Pct.	Std.Dev.
Market beta	1.11	1	1.1	1.22	0.2
Asset under Management (TASS)	564	100	250	630	958
Size of Equity Portfolio (13F)	477	75	190	440	867
Incentive Fee	19.61	20	20	20	2
Management Fee	1.3	1	1.2	1.5	0.32
Lockup Period	6.7	0	6	12	6.5
Redemption notice period	40	30	30	45	15.3
Leverage	0.35	0	0	1	0.47
High-Water Mark	0.81	1	1	1	0.38
Personal Capital	0.41	0	0	1	0.48

Table 2.3: **Risk Factors**

This table shows summary statistics for the different risk factor in % per month. The first factor is the Betting-against-beta factor of Frazzini and Pedersen [25]. The other factors are the excess return on the market (MKTRF),the small minus big factor (SMB); the excess returns on portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), the change in the constant maturity yield of the U.S. 10-year Treasury bond over the 3-month T-bill (BD10RET), the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond(BAAMTSY), the value factor (HML) of Fama and French [32], the Carhart [15] momentum factor (UMD), the Pastor and Stambaugh [33] liquidity risk factor and leverage mimicking factor (LMP) of Adrian et al. [45].

	Mean	Median	Stdev	Max	Min
BAB	0.43	0.49	1.24	4.11	-3.01
MKTRF	0.31	1.01	4.48	8.18	-18.54
SMB	0.16	-0.17	3.78	21.99	-16.85
BAAMTSY	0.02	-0.00	0.18	1.45	-0.25
BD10RET	-0.02	-0.04	0.24	0.68	-1.18
PTFSFX	0.85	-2.82	19.91	90.27	-30.13
PTFSCOM	0.20	-2.51	14.03	64.75	-23.04
PTFSBD	-0.80	-3.70	14.89	68.86	-25.36
HML	0.33	0.32	3.42	13.87	-12.37
UMD	0.87	0.77	5.06	18.35	-25.04
PS	0.74	0.51	3.54	10.98	-10.00
LMP	0.88	0.86	3.61	14.18	-18.57

TABLE 2.4: **Beta Arbitrage on the Investment Style Level**

This table reports results of time series regressions of hedge fund excess returns on the Fung and Hsieh Factors and the Betting against Beta (BAB) factor by investment style. The styles are Convertible Arbitrage (CA), Dedicated Short Bias (DSB), Emerging Markets(EM), Equity Market Neutral (EMN), Event Driven (ED), Fixed Income Arbitrage (FIA), Fund of Funds (FoF), Global Macro (GM), Long/Short Equity (LSE), Managed Futures (MF) and Multi Strategy (MS). The Fung and Hsieh factors are the excess return on the market (MKTRF),the small minus big factor (SMB); the excess returns on portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), the change in the constant maturity yield of the U.S. 10-year Treasury bond over the 3-month T-bill (BD10RET); and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond(BAAMTSY). Panel A reports results for the Fung and Hsieh Factors, Panel B the Fung and Hsieh Factors and BAB factor, Panel C uses the previous factors plus the leverage mimicking portfolio of Adrian et al. [45] (LMP) and the Pastor and Stambaugh [33] market liquidity risk factor. ***, **, * denote statistical significance at the 1%, 5% and 10% level.

	All Funds	CA	DS	EM	EMN	ED	FIA	GM	LSE	MF	EDMS	EDDS	EDRA	MS
						Fung and Hsieh 7 Factors								
MKTRF	0.286***	0.124***	-0.848***	0.516***	0.123***	0.220***	0.096***	0.193***	0.436***	-0.029	0.210***	0.238***	0.127***	0.105***
	(9.765)	(4.171)	(-18.053)	(8.059)	(2.782)	(10.533)	(3.763)	(3.749)	(14.173)	(-0.511)	(8.593)	(9.972)	(7.275)	(4.232)
SMB	0.111***	0.027	-0.311***	0.221***	-0.030	0.077***	0.001	0.020	0.258***	-0.007	0.094***	0.066**	0.066***	0.025
	(3.293)	(0.779)	(-5.753)	(3.000)	(-0.583)	(3.201)	(0.039)	(0.341)	(7.292)	(-0.101)	(3.337)	(2.410)	(3.280)	(0.885)
PTFSBD	-0.022**	-0.005	0.009	-0.043**	-0.021	-0.026***	-0.007	-0.020	-0.017*	0.041**	-0.027***	-0.025***	-0.016***	-0.001
	(-2.579)	(-0.596)	(0.655)	(-2.240)	(-1.582)	(-4.158)	(-0.942)	(-1.279)	(-1.811)	(2.433)	(-3.678)	(-3.523)	(-3.096)	(-0.191)
PTFSFX	0.008	-0.015**	-0.013	-0.016	0.008	-0.000	-0.020***	0.015	0.006	0.046***	0.000	-0.001	0.002	0.000
	(1.211)	(-2.129)	(-1.180)	(-1.088)	(0.806)	(-0.014)	(-3.318)	(1.216)	(0.876)	(3.516)	(0.047)	(-0.136)	(0.454)	(0.037)
PTFSCOM	0.015	-0.009	-0.025	0.013	0.017	0.002	0.002	0.016	0.011	0.036*	-0.003	0.006	-0.001	-0.002
	(1.578)	(-0.893)	(-1.632)	(0.623)	(1.150)	(0.284)	(0.194)	(0.952)	(1.070)	(1.962)	(-0.337)	(0.839)	(-0.232)	(-0.189)
BD10RET	-0.036	0.157**	-0.067	-0.037	0.574***	0.049	0.063	-0.141	-0.023	-0.090	-0.000	0.090	0.021	0.038
	(-0.488)	(2.080)	(-0.560)	(-0.224)	(5.077)	(0.915)	(0.973)	(-1.078)	(-0.294)	(-0.627)	(-0.004)	(1.481)	(0.484)	(0.600)
BAAMTSY	0.240**	0.448***	0.404***	0.178	1.279***	0.242***	0.446***	0.105	0.050	-0.035	0.175**	0.344***	0.022	0.319***
	(2.570)	(4.766)	(2.706)	(0.877)	(9.071)	(3.655)	(5.524)	(0.643)	(0.507)	(-0.197)	(2.261)	(4.543)	(0.399)	(4.042)
ALPHA	0.003**	0.002*	0.001	0.001	0.005***	0.004***	0.001	0.006***	0.003**	0.003	0.004***	0.005***	0.002***	0.003***
	(2.418)	(1.822)	(0.601)	(0.495)	(2.656)	(4.638)	(0.544)	(2.676)	(2.327)	(1.199)	(3.424)	(5.052)	(2.764)	(2.745)
R-squared	0.492	0.286	0.718	0.402	0.395	0.564	0.321	0.118	0.665	0.186	0.475	0.537	0.375	0.225

Beta Arbitrage on the Investment Style Level-Continued

	All Funds	CA	DS	EM	EMN	ED	FIA	GM	LSE	MF	EDMS	EDDS	EDRA	MS
	Fung and Hsieh 7 Factors plus Betting-against-Beta Factor													
MKTRF	0.318***	0.173***	-0.848***	0.580***	0.126***	0.251***	0.146***	0.234***	0.467***	0.012	0.239***	0.272***	0.140***	0.144***
	(10.621)	(6.018)	(-17.111)	(8.816)	(2.689)	(12.205)	(6.145)	(4.385)	(14.817)	(0.205)	(9.634)	(11.537)	(7.749)	(5.900)
SMB	0.105***	0.017	-0.311***	0.209***	-0.030	0.071***	-0.008	0.013	0.252***	-0.014	0.088***	0.059**	0.063***	0.018
	(3.207)	(0.547)	(-5.729)	(2.905)	(-0.590)	(3.144)	(-0.320)	(0.214)	(7.304)	(-0.221)	(3.256)	(2.300)	(3.193)	(0.666)
PTFSBD	-0.020**	-0.002	0.009	-0.039**	-0.021	-0.024***	-0.004	-0.017	-0.015	0.043***	-0.025***	-0.023***	-0.015***	-0.000
	(-2.417)	(-0.262)	(0.651)	(-2.077)	(-1.562)	(-4.081)	(-0.587)	(-1.124)	(-1.635)	(2.610)	(-3.548)	(-3.401)	(-2.966)	(-0.020)
PTFSFX	0.007	-0.016**	-0.013	-0.018	0.008	-0.001	-0.021***	0.013	0.005	0.045***	-0.001	-0.002	0.001	-0.001
	(1.098)	(-2.547)	(-1.176)	(-1.250)	(0.796)	(-0.231)	(-4.028)	(1.125)	(0.759)	(3.456)	(-0.115)	(-0.352)	(0.356)	(-0.155)
PTFSCOM	0.014	-0.010	-0.025	0.012	0.017	0.001	0.001	0.015	0.010	0.035*	-0.003	0.006	-0.002	-0.002
	(1.561)	(-1.072)	(-1.627)	(0.579)	(1.143)	(0.208)	(0.089)	(0.919)	(1.038)	(1.942)	(-0.420)	(0.799)	(-0.280)	(-0.263)
BD10RET	-0.066	0.111	-0.067	-0.095	0.571***	0.020	0.017	-0.179	-0.052	-0.127	-0.027	0.058	0.009	0.006
	(-0.898)	(1.588)	(-0.555)	(-0.592)	(5.009)	(0.392)	(0.288)	(-1.376)	(-0.672)	(-0.892)	(-0.441)	(1.004)	(0.208)	(0.105)
BAAMTSY	0.142	0.295***	0.404**	-0.017	1.271***	0.145**	0.291***	-0.021	-0.047	-0.161	0.087	0.236***	-0.019	0.198**
	(1.494)	(3.242)	(2.571)	(-0.084)	(8.572)	(2.219)	(3.857)	(-0.127)	(-0.468)	(-0.868)	(1.104)	(3.155)	(-0.336)	(2.551)
BAB	**0.363*** **	**0.569*** **	0.000	**0.728*** **	0.028	**0.362*** **	**0.579*** **	**0.472** **	**0.358*** **	**0.468** **	**0.330*** **	**0.401*** **	**0.154** **	**0.440*** **
	(3.406)	(5.552)	(0.002)	(3.107)	(0.166)	(4.939)	(6.833)	(2.477)	(3.188)	(2.242)	(3.742)	(4.763)	(2.384)	(5.060)
ALPHA	0.001	-0.001	0.001	-0.002	0.005**	0.002**	-0.002**	0.004	0.001	0.001	0.002*	0.003***	0.001	0.001
	(0.901)	(-0.441)	(0.547)	(-0.793)	(2.355)	(2.523)	(-2.205)	(1.482)	(0.894)	(0.202)	(1.734)	(2.976)	(1.597)	(0.598)
R-squared	0.524	0.395	0.718	0.434	0.395	0.618	0.467	0.149	0.683	0.209	0.515	0.591	0.395	0.328

TABLE 2.5: **Beta Arbitrage on the Individual Fund Level**

This table shows results for the time-series regressions on the individual fund level. For every hedge fund in the TASS database I run time series regressions of excess returns on theFung and Hsieh [30] seven factor model and the Fung and Hsieh [30] model plus the BAB factor of Frazzini and Pedersen [25]. The different rows show results for different requirement on the minimum number of observations for a fund to be included. Fraction(+) is the fraction of funds with a positive and significant factor loading on the BAB factor is significant (t-statistic¿1.645) and Fraction(-) the fraction with a negative and significant loading. 7 factor alpha is the median alpha of all funds using the Fung and Hsieh [30] model and the 8 factor alpha is the median alpha when the BAB factor is added.

	Funds	Fraction (+) (in %)	Fraction (-) (in %)	7 Factor Alpha (% per year)	8 Factor Alpha (% per year)
Panel A: Results for different required time series observations					
24	6505	27	5.6	4.1	2.5
36	5116	30.7	5.6	4.3	2.5
48	3920	32.6	5.8	4.4	2.8
60	2968	34.4	5.6	4.6	2.8
120	823	40	4.4	5.6	3.7
Panel B: Results by Investment Style					
Convertible Arbitrage	181	42.5	1.1	2.7	0.6
Dedicated Short Bias	36	8.3	5.5	6.1	6.7
Emerging Markets	427	52.2	0.7	7.1	1.7
Equity Market Neutral	329	30	5.4	2.4	1.1
Event Driven	490	45.9	3.3	4.6	2.5
Fixed Income Arbitrage	243	32.5	4.1	2.7	1.6
Global Macro	281	21	6.4	2.4	0.5
Long/Short Equity Hedge	2066	23.1	7.9	4.6	3.5
Managed Futures	543	22.5	5.7	6.1	3.7
Multi-Strategy	520	41.2	4.4	3.5	1.7

TABLE 2.6: **Beta factor sorted Portfolios**

At the beginning of each year hedge funds are sorted into ten equally weighted portfolios according to their loading on the BAB factor. The factor beta is calculated using a regression of hedge fund excess returns on the Fung and Hsieh [30] seven factor model and the BAB factor, using different minimum numbers of observations prior to portfolio formation. Portfolio returns begin in 1999 and end in December 2008. Columns 1 to 10 report the factor loadings on the the Fung and Hsieh [30] seven factor model and the alpha in % per month. The seven factors are the S&P 500 return minus risk free rate (MKTRF), the small minus big factor of Fama and French [32] (SMB), change in the constant maturity yield of the U.S.10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Column 11 report the same statistics for the 10-1 spread. t-statistics are in parentheses

Portfolio	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Fund Age ¿=36											
MKTRF	0.556	0.354	0.250	0.182	0.148	0.165	0.185	0.188	0.224	0.392	-0.164
	(13.078)	(10.179)	(8.473)	(8.209)	(7.011)	(7.038)	(6.707)	(6.558)	(6.004)	(6.936)	(-2.968)
SMB	0.396	0.284	0.140	0.112	0.074	0.046	0.019	0.041	0.005	-0.036	-0.432
	(10.052)	(8.811)	(5.118)	(5.468)	(3.792)	(2.111)	(0.748)	(1.549)	(0.147)	(-0.692)	(-8.437)
PTFSBD	0.005	-0.005	-0.007	-0.005	-0.009	-0.012	-0.012	-0.007	-0.001	-0.013	-0.018
	(0.396)	(-0.487)	(-0.809)	(-0.738)	(-1.589)	(-1.820)	(-1.533)	(-0.906)	(-0.112)	(-0.850)	(-1.173)
PTFSFX	0.011	0.009	0.013	0.005	0.004	0.003	0.008	0.012	0.018	0.014	0.003
	(1.157)	(1.154)	(1.876)	(1.082)	(0.822)	(0.478)	(1.223)	(1.866)	(2.151)	(1.085)	(0.219)
PTFSCOM	0.012	0.005	0.007	0.004	0.001	0.002	0.009	0.002	0.005	0.016	0.003
	(1.074)	(0.552)	(0.857)	(0.698)	(0.188)	(0.291)	(1.208)	(0.303)	(0.457)	(1.025)	(0.222)
BD10RET	-0.003	-0.003	-0.001	-0.010	-0.006	-0.009	-0.012	-0.006	-0.007	-0.008	-0.005
	(-0.442)	(-0.516)	(-0.215)	(-2.902)	(-1.949)	(-2.572)	(-2.902)	(-1.312)	(-1.307)	(-0.946)	(-0.627)
BAAMTSY	0.018	0.011	0.001	-0.007	-0.014	-0.020	-0.015	-0.023	-0.023	-0.039	-0.057
	(1.913)	(1.461)	(0.206)	(-1.409)	(-3.122)	(-3.959)	(-2.537)	(-3.639)	(-2.890)	(-3.207)	(-4.749)
Alpha	0.028	0.323	0.211	0.185	0.289	0.257	0.328	0.465	0.526	0.910	0.882
	(0.174)	(2.477)	(1.908)	(2.232)	(3.665)	(2.931)	(3.186)	(4.331)	(3.767)	(4.309)	(4.270)
Observations	120	120	120	120	120	120	120	120	120	120	120
R-squared	0.790	0.717	0.600	0.682	0.655	0.673	0.578	0.592	0.499	0.555	0.473
Panel B: Fund Age ¿=48											
Alpha	-0.010	0.307	0.194	0.248	0.296	0.221	0.363	0.411	0.486	0.978	0.988
	(-0.056)	(2.248)	(1.599)	(2.728)	(3.614)	(2.326)	(3.630)	(3.705)	(3.520)	(4.377)	(4.472)
Panel C: Fund Age ¿=60											
Alpha	-0.019	0.245	0.144	0.224	0.276	0.180	0.377	0.337	0.457	0.853	0.872
	(-0.106)	(1.533)	(1.103)	(2.506)	(2.905)	(1.961)	(3.514)	(2.830)	(3.271)	(3.682)	(3.778)

Table 2.7: **Robustness**

At the beginning of each year hedge funds are sorted into ten equally weighted portfolios according to their loading on the BAB factor. The factor beta is calculated using a regression of hedge fund excess returns on the Fung and Hsieh [30] seven factor model and the BAB factor, using different minimum numbers of observations prior to portfolio formation. Portfolio returns begin in 1999 and end in December 2008. Columns 1 to 10 report alpha per month (in %). The seven factors are the S&P 500 return minus risk free rate (MKTRF), the small minus big factor of Fama and French [32] (SMB), change in the constant maturity yield of the U.S.10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Column 11 report the same statistics for the 10-1 spread. t-statistics are in parentheses

Portfolio	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Controlling for Incubation and Backfill Bias											
Alpha	0.263	0.272	0.171	0.209	0.206	0.269	0.313	0.435	0.563	0.754	0.491
	(1.445)	(2.188)	(1.652)	(2.410)	(2.840)	(2.875)	(3.324)	(3.879)	(4.048)	(3.375)	(2.265)
Panel B: Controlling for Return Smoothing											
Alpha	0.287	0.288	0.051	0.274	0.272	0.266	0.335	0.545	0.561	0.765	0.478
	(1.609)	(2.517)	(0.534)	(3.573)	(3.236)	(3.142)	(3.690)	(4.699)	(4.057)	(3.346)	(2.111)
Panel C: Risk Adjustment with FH7 plus liquidity risk factor											
Alpha	0.226	0.262	0.165	0.192	0.209	0.226	0.218	0.372	0.340	0.607	0.381
	(1.498)	(2.122)	(1.715)	(2.051)	(2.340)	(2.370)	(2.056)	(3.286)	(2.537)	(3.054)	(2.316)
Panel D: Risk Adjustment with Fama and French 4 factor model											
Alpha	0.201	0.248	0.123	0.112	0.137	0.161	0.178	0.296	0.272	0.549	0.348
	(1.490)	(2.246)	(1.383)	(1.286)	(1.504)	(1.754)	(1.777)	(2.723)	(2.079)	(2.831)	(1.981)

Table 2.8: **Long/short equity funds**

At the beginning of each year long/short equity funds are sorted into ten equally weighted portfolios according to their loading on the BAB factor. The factor beta is calculated using a regression of hedge fund excess returns on the Fung and Hsieh [30] seven factor model and the BAB factor. Portfolio returns begin in 1999 and end in December 2008. Columns 1 to 10 report the alpha per month (in %). The seven factors are the S&P 500 return minus risk free rate (MKTRF), the small minus big factor of Fama and French [32] (SMB), change in the constant maturity yield of the U.S.10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Column 11 report the same statistics for the 10-1 spread. t-statistics are in parentheses

Portfolio	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Baseline Results											
Alpha	-0.084	0.119	0.296	0.236	0.126	0.315	0.225	0.552	0.565	1.171	1.255
	(-0.354)	(0.592)	(2.026)	(2.241)	(1.103)	(2.896)	(1.867)	(4.276)	(3.485)	(4.441)	(3.365)
Panel B: Adjusted for Backfill Bias											
Alpha	-0.030	0.093	0.140	0.273	0.238	0.149	0.312	0.487	0.807	0.974	1.003
	(-0.125)	(0.470)	(0.912)	(2.080)	(2.229)	(1.205)	(3.087)	(3.569)	(4.940)	(3.754)	(2.734)
Panel C: Adjusted for Return Smoothing											
Alpha	0.093	0.180	0.229	0.058	0.298	0.220	0.399	0.468	0.672	1.007	0.913
	(0.388)	(0.907)	(1.627)	(0.538)	(2.770)	(2.153)	(3.419)	(3.395)	(4.475)	(3.855)	(2.522)
Panel D: Fama and French											
Alpha	-0.084	0.303	0.375	0.304	0.113	0.283	0.112	0.414	0.346	0.776	0.659
	(-0.354)	(1.753)	(2.873)	(3.010)	(1.048)	(2.618)	(0.966)	(3.275)	(2.459)	(2.996)	(2.134)

Table 2.9: **Do hedge funds hold low beta securities?**

This table displays the summary statistics for market betas of the long equity holdings of funds in the different BAB factor sorted portfolios from Table 8. The sample is restricted to Long/Short Equity funds filing a SEC 13F report.

Portfolio	Average Beta	25th Pct.	Median	75th Pct.
1	1.26	1.05	1.23	1.43
2	1.22	1.06	1.19	1.34
3	1.22	1.03	1.14	1.36
4	1.16	1.02	1.14	1.26
5	1.19	1.07	1.16	1.32
6	1.18	1.01	1.14	1.31
7	1.10	0.99	1.10	1.20
8	1.09	0.96	1.06	1.25
9	1.09	0.92	1.08	1.23
10	1.09	0.78	1.03	1.22
10-1	0.17			
	(8.72)			

Table 2.10: **Which funds hold low beta stocks**

Regressions of hedge fund portfolio beta on fund characteristics. Portfolio beta is the value weighted average of the individual stock betas in a hedge fund portfolio. Individual stock betas are computed with daily data using the previous twelve month of data. The independent variables are a dummy for the use of leverage, the incentive fee in %, the management fee in %, a high-water mark dummy, a personal capital dummy, redemption notice period in days, the lock-up period in month, the VIX index and TED spread.T-statistics are in parentheses. ***,**,* denotes significance at the 1%, 5%, and 10% level respectively.

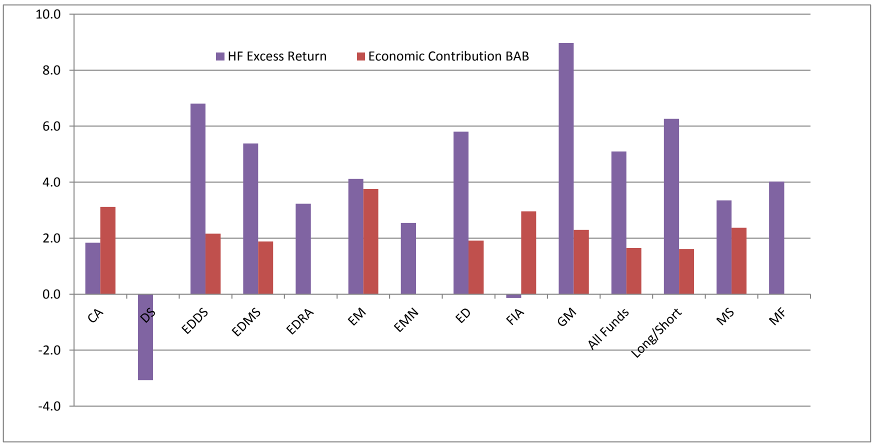
Leverage	-0.0307***	-0.0383***	-0.0371***	-0.0429***	-0.0410***	-0.0412***
	(-4.698)	(-6.090)	(-5.865)	(-6.904)	(-6.775)	(-6.877)
Incentive fee		0.0111***	0.0107***	0.0111***	0.0118***	0.0109***
		(5.949)	(5.661)	(5.984)	(6.204)	(5.751)
Management fee		0.0293***	0.0217*	0.0350***	0.0312***	0.0315***
		(2.959)	(2.021)	(3.393)	(3.162)	(3.217)
High-water mark			-0.0393***	-0.0299***	-0.0300***	-0.0315***
			(-4.692)	(-3.518)	(-3.657)	(-3.860)
Personal capital			-0.0205**	-0.0207**	-0.0167*	-0.0163*
			(-2.294)	(-2.406)	(-1.912)	(-1.848)
Redemption notice period				-0.0217**	-0.0164*	-0.0233**
				(-2.532)	(-1.876)	(-2.577)
Lockup period				-0.0785***	-0.0720***	-0.0733***
				(-5.357)	(-4.951)	(-5.042)
Size					0.0111***	0.00781**
					(3.672)	(2.706)
TED						0.000425***
						(4.295)
VIX						-0.00459***
						(-5.697)
Constant	1.127***	0.873***	0.934***	0.918***	0.689***	0.855***
	(137.3)	(18.35)	(17.83)	(18.46)	(7.113)	(9.174)
Observations	1,678	1,678	1,678	1,678	1,678	1,678
R-squared	0.006	0.022	0.029	0.045	0.051	0.087

Table 2.11: **Hedge Funds and other stock characteristics**

Regressions of different hedge fund portfolio characteristics on fund characteristics. The independent variables are a dummy for the use of leverage, the incentive fee in %, the management fee in %, a high-water mark dummy, a personal capital dummy, redemption notice period in days, the lock-up period in month, the VIX index and TED spread. T-statistics are in parentheses. ***,**,* denotes significance at the 1%, 5%, and 10% level respectively.

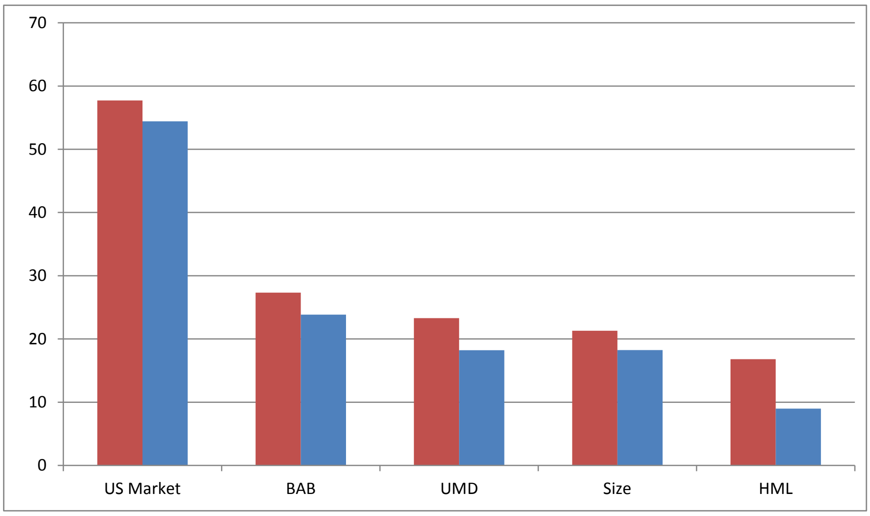
	Beta	Volatility	Book-to-Market	Momentum
Leverage	-0.0412***	-0.000700	-0.00644	0.0484**
	(-6.877)	(-0.439)	(-0.821)	(2.323)
Incentive fee	0.0109***	0.000806**	0.00392***	-0.00449
	(5.751)	(2.090)	(3.910)	(-1.286)
Management fee	0.0315***	0.0163***	-0.0185*	0.0756**
	(3.217)	(10.78)	(-1.757)	(2.155)
High-water mark	-0.0315***	-0.0119***	0.0452***	-0.143***
	(-3.860)	(-5.244)	(3.515)	(-4.415)
Personal capital	-0.0163*	-0.00172	0.0313***	-0.0262
	(-1.848)	(-0.958)	(4.889)	(-1.286)
Redemption notice period	-0.0233**	-0.00327*	0.0609***	-0.0632***
	(-2.577)	(-1.926)	(5.581)	(-3.051)
Lockup period	-0.0733***	-0.0130***	0.115***	-0.0377
	(-5.042)	(-4.932)	(4.305)	(-1.266)
Size	0.00781**	0.000437	-0.0167***	0.0210*
	(2.706)	(0.625)	(-4.134)	(1.762)
VIX	-0.00459***	0.00248***	0.00720***	-0.00891*
	(-5.697)	(4.952)	(4.138)	(-1.867)
TED	0.000425***	-0.000369***	-0.000194	4.72e-05
	(4.295)	(-6.752)	(-0.707)	(0.0593)
Constant	0.855***	0.0570***	0.519***	0.256
	(9.174)	(2.901)	(6.179)	(0.931)
Observations	1,678	1,678	1,678	1,678
R-squared	0.087	0.235	0.142	0.044

Figure 2.1: **Factor Selection on the Style Level**



This figure plots the average excess return of each investment style and the economic contribution of exposure to a beta arbitrage strategy to the average excess return. In a first step a stepwise regression procedure is used to extract the dominant benchmarks for each investment style from 12 available benchmark returns. The benchmark returns are the S&P 500 return minus the risk free rate, the small minus big and high-minus-low factors of Fama and French [32], the Pastor and Stambaugh [33] traded liquidity risk factor, the Carhart [15] momentum factor, leverage mimicking portfolio of Adrian et al. [45], the change in the constant maturity yield of the U.S.10-year Treasury bond adjusted for the duration of the 10-year bond, change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration, bond PTFS, currency PTFS , and commodities PTFS, where PTFS is primitive trend following strategy. The styles are Convertible Arbitrage (CA), Dedicated Short Bias (DSB), Emerging Markets (EM), Equity Market Neutral (EMN), Event Driven (ED), Fixed Income Arbitrage (FIA), Fund of Funds (FoF), Global Macro (GM), Long/Short Equity (LSE), Managed Futures (MF) and Multi Strategy (MS).

FIGURE 2.2: **Factor Selection on the Individual Fund Level**



This figure shows the five most often selected benchmark returns and the fraction of funds choosing them. For every hedge fund with a history of at least 36 month a stepwise regression is performed using 12 benchmark returns. The benchmark returns are the S&P 500 return minus the risk free rate, the small minus big and high-minus-low factors of Fama and French [32], the Pastor and Stambaugh [33] traded liquidity risk factor, the Carhart [15] momentum factor, the leverage mimicking portfolio of Adrian et al. [45], the change in the constant maturity yield of the U.S.10-year Treasury bond adjusted for the duration of the 10-year bond, change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration, bond PTFS, currency PTFS , and commodities PTFS, where PTFS is primitive trend following strategy.

Figure 2.3: **Hedge Fund Long Equity Beta**

This figure plots the value weighted beta of hedge fund long equity holdings and the value weighted beta of outstanding short interest from January 1999 to December 2008.

Chapter 3

Behavioral Factors in Risk Arbitrage

3.1 Introduction

Merger arbitrage strategies are investments in stocks of companies involved in a merger or acquisition (M&A). After the announcement of a takeover, the target stock usually trades at a discount to the price offered by the acquirer. A merger arbitrage strategy takes a long position in the target stock to eventually capture the spread between the current market price and the offer price in the event of deal completion. While the success probability of announced takeovers is very high, deals can and regularly do fail. Due to this deal completion risk, merger arbitrage is also known as risk arbitrage.[1]

Risk arbitrage is profitable. Mitchell and Pulvino [53] as well as Baker and Savasoglu [54] document significant risk-adjusted returns in risk arbitrage and postulate that the abnormal returns are compensation for providing liquidity to exiting shareholders. Assuming demand curves for stocks are not perfectly elastic, i.e. there are limits to arbitrage, selling pressure by target shareholders pushes prices below their fundamental value and generates a profitable trading opportunity for investors willing and able to provide liquidity. So far, the literature however lacks a full and satisfactory explanation for the

[1] In the rest of the paper the terms risk arbitrage and merger arbitrage are used interchangeably.

liquidity demand of target shareholders after the takeover announcement.[2] Therefore, our understanding of the profitability of merger arbitrage is incomplete.

Drawing on the literature of psychological anchors (Tversky and Kahneman [56]) and prospect theory (Kahneman and Tversky [57]), Baker et al. [58] provide significant empirical evidence for the importance of behavioral biases in the takeover market. In particular, they document a clustering of offer prices in takeovers around recent peak prices and they find a jump in the success probability of a takeover for offer prices only slightly exceeding the target stock's 52-week high.[3] Besides the aforementioned results, the work of Baker et al. [58] also shows a promising direction to look for an explanation of merger arbitrage profitability.

The idea is the following: Investors prone to behavioral biases sell the target stock when the offer price is above the 52-week and their liquidity demand is absorbed by risk arbitrageurs. This, by the way, leads to a higher fraction of risk arbitrageurs in the shareholder base. As risk arbitrageurs are more likely to accept a takeover offer, their presence increases the success probability of a takeover (Cornelli and Li [59], Hsieh and Walkling [60]). Risk arbitrageurs are however also risk averse and have a limited amount of capital. Thus, to provide liquidity to the selling shareholders, they require a compensation even for idiosyncratic risk (Baker and Savasoglu [54]). Drawing on this idea, a large portion of the abnormal returns in merger arbitrage should be concentrated in takeover deals with offer prices above the target stock's 52-week high.

Note that the results of Baker et al. [58] do not imply this explanation for merger arbitrage profits. On the one hand, they do not examine the trading behavior of investors. This means that it is unclear whether offer prices above the 52-week high trigger any selling pressure. The higher deal success probability for offer prices above the target stock's 52-week high can also be consistent with channels different from the aforementioned one. On the other hand, their results could even predict the opposite. A higher success probability decreases the risk of a takeover deal and therefore, risk arbitrageurs

[2] Direct empirical evidence exploring the determinants of investor exit around takeover announcements is scarce. Using institutional trade-level data, Jegadeesh and Tang [55] suggest that one important motive to trade, portfolio rebalancing, cannot explain the investor exit after takeover announcements.

[3] Although the authors stress that the 52-week is not the *magic* number and there are other peak prices with incremental importance in merger negotiations, they provide significant empirical evidence highlighting the role of this *specific* price level.

require a lower compensation to absorb the shares of selling shareholders. Hence, it is an open empirical question whether the behavioral bias identified by Baker et al. [58] also offers an explanation for the profitability of merger arbitrage.

This paper empirically tests this explanation. First, I ask whether offer prices above the 52-week high trigger selling pressure by investors. To do so, I use institutional trading data provided by Ancerno. Most behavioral effects are empirically examined using data on individual investor trading (for example Odean [61]).[4] The rising amount of equity held by institutional investors makes an understanding of this group's trading behavior however increasingly important.

I find that institutional investors are selling on average 50% more of the target stock at the announcement date if the offer price exceeds the target stock's 52-week high. While slightly lower in magnitude, this effect also prevails in the days after the announcement day. The economic magnitude of the effect is even stronger when I use the more robust median. Using the median, institutional investor exit from the target for offer prices above the 52-week high exceeds institutional investor exit for offer prices below the 52-week high by more than 100% at the announcement date. The effect statistically and economically survives after controlling for the offer premium, the size of the target, acquirer characteristics, other deal characteristics and time fixed effects.

Second, I test whether offer prices exceeding the 52-week high predict higher returns in a sample of over 7000 takeover deals in the US and across 23 developed countries in the period from 1985 to 2012. At the beginning of each month I sort all takeover deals into three portfolio depending on the distance between the offer price and the target stock's 52 week high ($\Delta 52$). A trading strategy investing in takeover deals in the highest tercile generates annual abnormal returns of 7.4% in the period between 1985 and 2012. To the contrary, a trading strategy investing in takeover deals in the lowest tercile does not generate any abnormal returns. Thus, consistent with the proposed explanation, risk arbitrage profits are fully concentrated in takeovers with offer prices above the 52-week high.

[4]One of the exceptions is Frazzini [62]

I rule out several other explanations of my results. I find that my results survive when I use different asset pricing models to compute risk-adjusted returns. Furthermore, I show that other variables, correlated with $\Delta 52$, are not driving out the results. Specifically, neither the offer premium, an important predictor of risk arbitrage returns proposed by Baker and Savasoglu [54], nor the disposition effect can explain my results.

Having established a robust unconditional relation between risk arbitrage returns and offer prices above the 52-week high, I study their conditional relation. In particular, I analyze whether the return predictive power of $\Delta 52$ varies systematically with the supply of arbitrage capital.

To proxy for the amount of available arbitrage capital, I build on the following idea: It is a well-known fact that mergers and acquisitions occur in cycles (see e.g. Shleifer and Vishny [63]). If capital is slowly moving into and out of merger arbitrage funds, there will be an oversupply of arbitrage capital at times of low deal activity growth and an undersupply of arbitrage capital at times of high deal activity growth.[5] Using the growth in takeover activity as a proxy for the supply of arbitrage capital, I find the predictive power of $\Delta 52$ to be significantly higher at times when arbitrage capital is scarce.

I provide several additional results in the paper. First, I investigate the role of transaction costs. I compute risk arbitrage returns adjusted for costs arising through the bid-ask spread using the estimator of Corwin and Schultz [65] and I estimate trading cost functions from trade level data following Keim and Madhavan [66] and Moskowitz et al. [67]. I find that trading costs for takeover targets are low and risk-arbitrage strategies based on $\Delta 52$ exhibit significant scalability.[6]

Second, I study the investment value of the variable $\Delta 52$ in a portfolio setting using the parametric portfolio policy approach proposed by Brandt et al. [68]. Brandt et al. [68] estimate optimal portfolio weights as functions of asset characteristics. The approach of Brandt et al. [68] allows me to evaluate the economic importance of the 52-week

[5]Such a mechanism can be motivated for example with the work of Pastor and Stambaugh [64]. In their model investors slowly learn and update their beliefs about the returns from active management. Due to this slow updating of beliefs investor capital does not react sufficiently as a response to a changing investment opportunity set.

[6]They decrease by around 50% in the post-announcement period compared to the pre-announcement period

high from the perspective of a risk arbitrageur after controlling for several other return predictors in takeovers. Assuming an investor with constant relative risk aversion $\gamma = 4$ and imposing a no-short sale constraint, I estimate significant utility gains in- and out-of sample when the investor incorporates the difference between the offer price and the target stock 's 52-week high in his portfolio decision. Furthermore, other variables and transaction costs are not driving out the effect.

This paper contributes to the literature in several ways. First, it complements the results of Baker et al. [58]. One can argue the effect of the 52-week high on merger pricing and merger outcomes are mainly due to its impact on small investors where behavioral biases are more present. Indeed, Baker et al. [58] provide evidence suggesting that in the more recent half of their sample, where the amount of equity held by institutional investors already increased significantly, offer prices seem to be somewhat less influenced by the 52-week high. My evidence however suggests that the 52-week high also affects institutional investors. Thus, the results of Baker et al. [58] may not only be important in their sample period, but also going forward. Additionally, the paper provides results concerning the impact of offer prices exceeding the 52-week high on another aspect of the takeover market, risk arbitrage profits. As pointed out earlier, the impact on risk arbitrage profits is ex ante not clear.

Second, the paper contributes to the growing literature documenting significant shifts in asset supply or demand around a stock's 52-week high. George and Hwang [69] find that a stock's nearness to its 52-week high explains most of the returns to momentum investing and Heath et al. [70] find a doubling of employee option exercise when a stock exceeds its 52-week high. Two contemporaneous papers by Birru [71] and George et al. [72] study the relation between a stock's 52-week high and the earnings announcement drift. Both studies find a significant earnings announcement drift only for stocks trading near their 52-week highs and interpret this result as evidence for psychological anchoring.

Third, to the best of my knowledge this is the first paper to study returns in risk arbitrage using an international sample of takeovers. Most studies on risk arbitrage returns focus on the US market (e.g. Mitchell and Pulvino [53], Baker and Savasoglu [54]) or study another market in isolation. Most risk arbitrage funds however invest globally. Studying risk arbitrage using a global sample therefore provides better insights into the performance of this alternative investment strategy.

Fourth, the paper provides transaction cost estimates for trading takeover targets and analyzes the scalability of risk arbitrage strategies. In their seminal paper Mitchell and Pulvino [53] use transaction cost estimates provided by Breen et al. [73]. They note however, that trading costs can be different during merger situations. This paper empirically shows that the trading costs of merger stocks are indeed very different.

Fifth, the paper investigates the usefulness of the Brandt et al. [68] parametric portfolio policy approach for event-driven investment strategies.[7]

The remainder of this paper is structured as follows. Section 1 reviews theory which motivates the relation between a stock's 52-week high, trading decisions and asset prices. Section 2 describes the data sources, section 3 studies investors' trading behavior around takeover announcements, section 4 studies the impact of recent peak prices on risk arbitrage returns, section 5 provides additional results and section 6 concludes.

3.2 Background and Motivation

The 52-week high is a salient price level. It is mostly irrelevant, but highly visible as it is usually reported in the finance section of every major newspaper (for example the Wall Street Journal). Experimental evidence of Tversky and Kahneman [56] suggests that such salient and often irrelevant information can have a major influence when individuals have to perform complex tasks like estimating a quantity. Specifically, according to Tversky and Kahneman [56] individuals often anchor on salient information. In the case of stocks, investors may use as an initial estimate for the fair price the 52-week high and afterwards they incorporate other information into their estimate. The final estimate usually does not deviate too much from the initial value however. Hence, individuals seem to anchor on the initial value.

[7]The Brandt et al. [68] approach has already been applied in Plazzi et al. [74] for real estate portfolios, in Ghysels et al. [75] for international asset allocation and in Barroso and Santa-Clara [76] for currency investments. The results of all these studies suggest that the Brandt et al. [68] approach is robust, delivers good out of sample results and is often superior to traditional portfolio optimization methods despite potential model mis-specifications.

How does this impact the trading decisions of investors around a takeover announcement? Takeover announcements are good news for target shareholders and the stock price increase due to the takeover announcements usually grabs investor attention. According to Ben-David and Hirshleifer [77] this can lead many investors to re-examine their positions and trade depending on their beliefs concerning the stock. An offer price significantly exceeding the 52-week high pushes the market price of the stock above the 52-week high and when investors anchor on the 52-week high, they may sell their positions in the target stock as (1) they believe the investment has run its course, (2) they do not expect high returns going forward as the offered price is already above the estimated fair value and hence, higher offers are unlikely.

A different explanation for observing increased liquidity demand around the 52-week high is based not on beliefs, but on values. Prospect theory proposed by Kahneman and Tversky [57] provides an alternative theory of decision making under risk to the standard expected utility theory. Importantly, prospect theory assumes individuals evaluate outcomes relative to a reference point, they have a greater aversion to losses than they appreciate gains and their sensitivity to changes in an outcome decreases the further away the outcome moves away from the reference point. These assumptions imply a utility function which is concave in the region of gains and convex in the region of losses. The reference point in prospect theory is not well defined and can be the status quo, an expectation or an aspirational level. In finance, empirical evidence (Heath et al. [70]) as well as experimental evidence (Gneezy [78]) however suggests a stock's 52-week high is one important reference point. Thus, when the stock price moves above the 52-week high investors are pushed into the concave region of their utility function, which increases their risk aversion and their propensity to sell.

Finally, recent work by Barberis and Xiong [79] provide a third motivation for observing an increased liquidity demand for offer prices exceeding the 52-week high. Barberis and Xiong [80] examine theoretically the ability of prospect theory to predict the disposition effect (see Shefrin and Statman [81]) and raise doubts. Empirically, individual stock returns are positively skewed whereas market returns are negatively skewed (see e.g. Hong and Stein [82]). In particular with a positively skewed return distribution, prospect theory, according to Barberis and Xiong [80], often predicts the opposite of a disposition effect. In Barberis and Xiong [79] the authors therefore propose a new theory based on the realization utility hypothesis. According to this hypothesis made by Shefrin and Statman [81] investors experience a direct utility (disutility) from realizing gains (losses). Assuming a sufficiently high discount rate, investors with realization utility preferences exhibit a disposition effect. Furthermore, the model of Barberis and Xiong [79] predicts increased selling intensity around a stock's 52-week high.

3.3 Data

3.3.1 Data on Mergers and Acquisitions

I use data on mergers and acquisitions from the Thomson SDC database between 1985 and 2012. The SDC database covers mergers and acquisitions around the world. In this paper I restrict the sample to a set of 23 developed countries. Specifically, I use data from the US, Canada, Australia, New Zealand, Hong Kong, Singapore, Japan, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.
For my final sample I apply the following filters to the dataset:

- In the US I only keep deals where I am able match the cusip of the target provided by SDC with the CRSP daily tapes. For all other countries I require a valid match between a target's cusip (Canada), sedol (rest of the world) or name with the Compustat Global Security Daily files. For equity financed deals I furthermore require a valid match between the acquirer's cusip, sedol or name and CRSP or Compustat.
- A deal has to be pure cash or pure stock financed. For stock financed deals I require a valid exchange ratio from SDC. In case of missing exchange ratios I checked manually whether the exchange ratio is stated in the SDC deal synopsis.
- Although I checked the match between SDC and the different databases manually, there are some unreasonable matches. Several deals report negative bid premia,

initial arbitrage spreads of more than 100% or smaller than -20%. I delete these observations from the sample.

- Merger Arbitrage is a mid to small cap strategy. I delete however deals with a value of less than USD 10 million to guarantee that my results are not contaminated by extremely illiquid securities.

After applying the aforementioned filters I have a sample of 7740 takeover transactions. With 4888 transactions most of the deals in my sample take place in the US. This is however mainly due to the overrepresentation of US deals in the early part of the sample. Takeover transactions outside of the United States became increasingly important in the more recent period. The top graph of Figure 1 shows the number of deals and the bottom graph of Figure 1 the volume of deals for the US sample and the international sample excluding the US. Until 2005 over 50% of all deals as well as 50% of all deal volume occurred inside the United States. Afterwards the number and volume of takeover transactions outside the US outpaced deal volume inside the US.

The impact of the financial crisis on the takeover market is clearly visible in Figure 1. The total value of announced takeover deals was around USD 700 billion in 2007 and dropped to USD 100 billion in 2009. The deterioration in credit market conditions increased the financing costs of acquisitions and the macroeconomic uncertainty led many companies to postpone larger investments like acquisitions. The minimum of takeover volume in my whole sample occurred in 1991 with a volume of just USD 11 billion when the takeover market had to recover from the junk bond financed merger wave of the late 1980s. The maximum of takeover volume is in 2007 with USD 710 billion. In terms of number of deals the minimum is in 1991 and the maximum in 1999.

Table 1 shows summary statistics for the total sample of takeover deals as well as for takeover deals inside and outside of the United States. The first row of Table 1 shows the offer premium computed as $(OP-P)/P$, where OP is the offer price and P the stock price 20 days prior to the announcement date. The average takeover premium is 39.5% and a comparison between Panel B and Panel C suggests a slightly higher premium paid for US companies compared to companies outside of the US. The second row of Table

1 presents the difference between the offer price and the 52-week high of the target company's stock scaled by the 52-week high. The 52-week high is thereby computed as the highest stock price of the target from 385 days before the announcement until 20 days before the announcement. On average acquirers pay a premium 2.5% above the 52-week high of the stock. This result is in line with the work of Baker et al. [58] showing a clustering of offer prices slightly above the 52-week high. Also when the 52-week high is used as a reference point to determine the offer premium, prices paid to US target shareholders seem to be more favorable compared to other countries. Shareholder protection in the US is in general better compared to other countries, which can be an explanation for the differences in premiums paid to target shareholders.

Most of the other deal characteristics do not show interesting differences between the US and other countries. Around 13% of deals are leveraged buy-outs, 6% of the deals are hostile, 20% of the deals are financed with stock and for 40% of the deals the acquirer is private. The only deal characteristic being significantly different between the US and international markets is the number of tender offers. In the US only 32% of takeover deals are classified as tender offer whereas 66.7% of the deals outside of the US are tender offers. Compared to a merger or acquisition agreement target shareholders are approached directly by the acquirer in a tender offer. A tender offer has the advantage of a higher speed of execution and a higher chance of shareholder approval. Therefore it should be the preferred form for an acquisition bid. A reason for the lower share of tender offers in the US compared to other countries can be the "Best Price Rule". In order to curb the practice of greemailing during the hostile takeover wave of the 1980s the Securities and Exchange Commision (SEC) introduced the "Best Price Rule". This rule forces an acquirer to pay the same price per share for every shareholder including the management of the company. Crucially, this also included employment compensation, severance or other employee benefit arrangements of security holders of the target. Due to these strict requirements tender offers became less attractive for bidders beginning in 1986. In 2006 the "Best Price Rule" was amended to exempt the aforementioned items which led to a significant increase in the number of tender offers afterwards.

3.3.2 Institutional Trading Data

I obtain institutional trading data from Ancerno, a trading cost consultant. The sample period of the Ancerno data spans the period from January 1999 to December 2010 and the analysis focuses on data for the U.S. equity market. As a stock identifier Ancerno provides a cusip which allows me to match the institutional trading data to my sample of takeovers from SDC. I am able to match 1601 takeover transactions and Table 2 provides summary statistics for this subsample of transactions.

A visual inspection suggests that the distribution of deal characteristics is very similar to the broader sample reported in Table 1 Panel 3. With an average market capitalization of USD 990 million targets in the sample matched with Ancerno are however larger than targets in the broader sample (average market capitalizaion USD 723 million). As the average target size grows over time the larger target size is due to the shorter time period of the matched sample. Another explanation is the preference of institutional investors for larger stocks reported by for example Gompers and Metrick [83].

The Ancerno database is used by several recent academic studies including Puckett and Yan [84], Franzoni and Plazzi [85] and Jegadeesh and Tang [55]. Ancerno receives data either from pension funds or directly from money managers. The institution sending the data is identified with the clientcode, but Ancerno also provides a managercode identifying the institution managing the assets. Following prior literature this paper focuses on the institution managing the assets and I define a daily trade as the aggregation of all executions in the same stock, at the same side and at the same date by one manager. For every trade Ancerno provides several variables besides the already mentioned ones including the execution price and the commisions paid.

Panels B to D provide summary statistics for the trading of institutional investors in takeover targets during the period from -200 days before the announcement until the completion or the withdrawal of the takeover. Takeover deals are kept in the sample until a maximum of 200 days after the announcement. The different panels present statistics separately for the full sample, the pre-announcement and post-announcement period. My full sample includes a total of 728 different managers. For a single deal, on average 16 to 25 of them are trading the target stock and the average trade size is between USD 1 million and USD 1.4 million. The distribution of the dollar trade volume is however highly skewed with the median dollar trade being between USD 68000 and USD 93000.

Besides the amount of institutional trading another interest of this paper are also the trading costs of institutional investors before and during the takeover deal. Trading costs can be split into two parts. The first part are the commisions paid for the execution of the trade. Panels B to D suggest that average commisions are equal to 10 basis points of the stock price and median commisions are around 5 basis points. The second part are price impact costs. Similar to Anand et al. [86], I use the execution shortfall to measure price impact costs. Execution shortfall is defined as

$$ES(t) = \frac{P_l(t) - P_0(t)}{P_0(t)} D(t),$$

where $P_l(t)$ is the volume-weighted execution price, $P_0(t)$ is last day's closing price of the stock and $D(t)$ is a categorical variable equal to 1 for buy trades and equal to -1 for sell trades. Anand et al. [86] use the opening price of the stock as a pre-trade benchmark. The difference between using the last day's closing price and the opening price are however negligible. Panels B to D of Table 2 suggest institutional investors' price impact costs are around 4 basis point before the announcement, 2 basis points after the announcement and around 3 basis points for the full sample.

3.4 Institutional Exit and the 52-Week High

This section examines the trading behavior of institutional investors around takeover announcements and tests whether offer prices exceeding the 52-week high lead to an excessive liquidity demand from institutional investors. Following Jegadeesh and Tang [55] I study the net trading volume of institutional investors defined as the dollar volume bought minus dollar volume sold divided by the market capitalization of the stock.

Figure 2 plots the net trading volume of institutional investors from -10 days to +10 days around the takeover announcement for offer price below and above the 52 week high. In order to ensure that the results are not driven by outliers the top graph of Figure 2 shows the average net trading volume and the bottom graph shows the more robust median. Figure 2 does not exhibit a particular trading pattern in the pre-announcement period. The mean net trading volume seems to be slightly negative and the median is close to zero for both sub-groups. After the announcement institutional investors sell large amounts of their holdings in the target stock in particular when the offer price is above the 52-week high. At the announcement date institutional investors sell around 0.6% of the target company for offer prices above the 52-week and 0.4% for offer prices below the 52-week high. Thus, offer prices exceeding the target stock's 52-week high increase the trade imbalance by 50%. The median shown in the bottom graph draws an even clearer picture with institutional investors selling 2.4 times more when the offer price exceeds the 52-week high. The difference in the trade imbalance among these two sub-groups does not vanish after the announcement date. Indeed, institutional investors sell more given the offer price is above the chosen reference point on every day after the announcement date.

The univariate results are in line with the hypothesis that offer prices above the target stock's 52-week high lead to an excessive liquidity demand. To test whether the effect is significant after controlling for other drivers of the trading behavior of institutional investors after and at the announcement I use multivariate regressions in Table 3. The dependent variable in the regressions is the cumulated net trading volume between the announcement date and the 10th day after the announcement. In column 1 a dummy equal to one for offer prices above the 52-week high is used as an independent variable. For offer prices above the 52-week high institutional investors sell 0.8% more of the target company at the announcement date and in the first 10 trading days after the announcement. In column 3 I use the difference between the offer price and the 52-week high. The results suggest an increase of institutional selling of 0.1% for an increase of the offer price of 10% compared to the 52 week high. Columns 5 and 7 of Table 3 repeat the results including time fixed effects without a significant change in the results.

Jegadeesh and Tang [55] find a number of other deal characteristics correlated with the magnitude of institutional selling after the announcement date. First, I include the offer premium measured as the difference between the offer price and the stock price 20 days before the takeover announcement. Baker and Savasoglu [54] use the offer premium as a measure of the downside risk of a takeover deal. If investors care about downside risk and measure the downside relative to the stock price 20 days before the announcement date, they will sell more target stocks depending on the size of the offer premium. Column 2 of Table 3 however does not show a significant effect of the offer premium on net trading volume of institutional investors.

A positive and significant effect has the stockdeal dummy. Jegadeesh and Tang [55] suggest that some funds are considering the acquirers as attractive investment. Therefore, the funds hold on to their target stocks which are eventually converted into acquirer stocks. Another interpretation of this result are tax considerations. If an institutional investor invested in the target stock less than 12 month before the announcement, he would decrease his capital gains taxes by staying invested in the target stock until his investment is only taxed with the lower long-term capital gains tax. This can even imply an eventual exchange of target stock into acquirer stock. Of course, this argument applies mainly to institutional investors having bought the target stock in the recent past, i.e. between 1 and 6 months before the announcement. The average takeover deals closes after 100 days or around 5 month. Hence, for an investor having bought the target stock 10 month before the announcement it is advantageous from a tax view not to sell immediately even in a cash deal.

In line with Jegadeesh and Tang [55] the size of the takeover deal negatively impacts institutional trading around the takeover announcement. Column 2 of Table 3 does not include time fixed effects. Column 4 of Table 3 however does and after controlling for time fixed effects the tender offer dummy has a negative and significant impact on the amount of institutional trading. As already mentioned earlier due to less regulatory burdens tender offers are executed at a faster speed compared to other deal structures. Furthermore, as a consequence of the faster execution, competing offers are less likely.

Institutional investors may therefore expect low expected returns going forward and exit their investments in the target stocks.

The final three deal characteristics included in the regressions of table 3 are a dummy for hostile bids, a dummy for private acquirers and a dummy for leveraged buyouts. The leveraged buyout dummy and the hostile dummy are insignificant. The private acquirer dummy however is highly significant. Thus, institutional investors appear to be reluctant to exit the target stock conditional on the acquirer being private. Bargeron et al. [87] find that private acquirers pay significantly lower premiums compared to public acquirers. If target shareholders expect a competing offer due to the low premium offered by a private acquirer, they may hold on to their investment in the target stock.

3.5 The 52-Week High and Risk Arbitrage Returns

3.5.1 Baseline Results

Using portfolio sorts this section examines whether the increased price pressure for offer prices above the 52-week high predicts high future abnormal returns due to a limited number of risk averse arbitrageurs. Every month I sort takeover deals according to the distance between the offer price and the 52-week high into three portfolios and track the portfolios' performance over time.

For the return computation of each individual deal I follow Mitchell and Pulvino [53]. The daily return in USD on cash deal i at time t is the target return reported in CRSP or Compustat Global $r_{it} = r_{Tit}$. For a stock deal the return computation is more complicated as it includes a short position in the acquirer stock. The merger arbitrage return in a stock transaction is given by $r_{it} = r_{Tit} - \delta(r_{Ait} - r_{ft})\frac{P_{Ait-1}}{P_{Tit-1}}$, where δ is the exchange ratio, r_{Tit} the target stock return, r_{Ait} the acquirer stock return, r_{ft} is the risk free rate, P_{Ait-1} and P_{Tit-1} are the acquirer stock price and the target stock price. I assume that the risk arbitrageur is earning the risk free rate as a short rebate. Afterwards monthly returns are computed by compounding daily returns for every transaction. In the portfolio analysis I define a deal as investable if it was announced before the beginning of the month. In case a deal is not active for the whole month, i.e. the deal closes before the end of the month, I use the risk-free rate for the non-active days of the month. [8]

Finally, I have to compute the performance of the portfolio of all transactions. Mitchell and Pulvino [53] and Baker and Savasoglu [54] report portfolio returns for a value-weighted or equal weighted portfolio of risk arbitrage situations.[9] Equal-weighting the returns leads to well-diversified portfolios with high-weights on small and less liquid deals. Value-weighting the returns leads to a tilt towards larger and more liquid deals. The resulting portfolios are however not well diversified. In my sample the largest transaction often has a weight of more than 40%. In order to have well-diversified portfolios tilted towards larger deals I construct rank-weighted portfolios. For the rank-weighted portfolios the weight of deal i at time t is

$$w_{i,t} = \frac{rank(size_{i,t})}{\sum_{i=1}^{N} rank(size_{i,t})}.$$

Using these weights I compute every month the rank weighted return of all active takeover deals.

Panel A of Table 4 shows risk-adjusted returns (alpha) for rank-weighted portfolios using the US sample of risk arbitrage situations. For the risk-adjustment I use the three Fama and French [32] factors and the Carhart [15] momentum factor. Using the four factor model the portfolio in the lowest tercile and the middle tercile have insignificant alphas of 0.05% and 0.14% monthly. The highest tercile to the contrary generates an alpha of 0.58% monthly. With a monthly alpha of 0.53%, a long-short portfolio going long the highest tercile and short the lowest tercile provides economically significant risk-adjusted returns. With a t-statistic of 2.85 the long-short portfolio is also statistically significant. I interpret these results as evidence for stock price underreaction as a consequence of the selling pressure documented in the previous section.

Panel B of Table 4 shows portfolio returns for the international sample and Panel C for an international sample excluding the United States. Enlarging the sample decreases

[8] Mitchell and Pulvino [53] assume a zero return for non-active days. Following this rule does not change the results of my analysis

[9] Mitchell and Pulvino [53] also report results imposing a diversification constraint where the maximum weight of a deal is restricted to 10%.

idiosyncratic noise in the portfolios and increases the statistical power of the tests. Thus, while the economic magnitude of the return spread between the high and low portfolio stays nearly the same in Panel B, the statistical significance increases. Panel C of Table 4 suggests that the results also hold outside of the United States. The small number of deals before 1999 does not allow the construction of diversified portfolios. Panel C therefore focuses on the period after 1998. Despite differences in the time period the results inside and outside of the United States look very similar.

The results in Table 4 are conservative estimates. First, there is only an investment in a takeover transaction when the transaction was announced before the beginning of the month. Price pressure is particularly strong in the first days following the announcement. An extended lag between the announcement of the deal and the investment into the deal can therefore mean that returns due to a decreasing spread are missed out. Second, the hypothetical portfolios have often large cash holdings. I assume deals becoming inactive during the month earn the risk-free rate for the rest of the month, i.e. the proceeds of for example a closing of a deal are invested in a cash-like asset. Around 20% of all deals become inactive each month. The large cash holdings can understate the returns for an investor rebalancing his portfolio in a more timely manner. Column 1 to 4 of Table 5 therefore show results using a different methodology to aggregate returns. Specifically, I follow Baker and Savasoglu [54] and aggregate first the returns across all deals at the daily level level and then aggregate the resulting portfolio return on the monthly level. The results are qualitatively similar to the results reported in Table 4 Panel B, but economically and statistically stronger. Additionally columns 5 to 8 also reports portfolio returns using value-weights instead of the rank weights. The results remain economically the same, but the statistical significance decreases which I attribute to the aforementioned decreased diversification of the portfolios.

3.5.2 The Role of Risk

In the previous section I assume the Carhart [15] four factor model to be the correct asset pricing model. While the Carhart [15] four factor model is one of the most used asset pricing models in the academic literature, the more recent literature finds a host of other factors explaining the time-series and cross-sectional behavior of asset returns. In particular since the most recent financial crisis beginning in 2008 asset pricing models taking into account systematic exposure to market liquidity risk, funding liquidity risk, tail risk and downside risk gained popularity.

On theoretical grounds systematic market liquidity risk seems to be a well motivated factor to explain the returns of risk-arbitrage investments. Investors require a risk premium for assets whose liquidity comoves positively with market wide liquidity. In the model of Brunnermeier and Pedersen [46] exposure to liquidity risk can in particular occur in the presence of many leveraged investors. In their model funding liquidity shocks due to sudden investor redemptions or changes in margin constraints can lead to a sudden decrease in market liquidity when leveraged investors have to liquidate their positions in a very short period time. The main investors in the risk arbitrage market are proprietary desks of investment banks and hedge funds. Hence, according to the theory of Brunnermeier and Pedersen [46] there should be a strong link between market and funding liquidity in the risk arbitrage market and the systematic liquidity risk should explain parts of the returns in this market.

In column 1 of Table 6 I add the funding liquidity risk factor of Adrian et al. [45]. Adrian et al. [45] propose an asset pricing model where expected returns depend on an asset's covariance with shocks to the leverage of financial intermediaries. The authors argue that as leveraged financial intermediaries are most of the time the marginal investors in financial markets asset prices are closely tied to their marginal value of wealth. The marginal value of wealth of a financial intermediary on the other hand depends on its funding capacity. Hence, the authors propose a stochastic discount factor, which is linear in the leverage of financial intermediaries and demonstrate empirically its strong pricing ability in the cross-section of asset return. Furthermore, to allow time-series tests the authors construct a leverage mimicking portfolio (LMP). I add the LMP as an additional factor to test its explanatory power for the spread portfolio. The results reported in column 1 of Table 6 suggest that the LMP factor is not able to explain the return spread. The same holds when I use a market liquidity risk factor instead of a funding liquidity risk factor. In columns 2 I add the traded liquidity risk factor of

Pastor and Stambaugh [33] to the Fama and French [32] three factors and the Carhart [15] momentum factor. The results in Table 6 suggest that there is only a weak link between market liquidity risk and the spread portfolio.

I use a global sample of risk arbitrage situations, but use a local asset pricing model. In column 3 of Table 6 I use global versions of the Fama and French [32] and the Carhart [15] factors. [10] The results using the global factors span a shorter time period as they are only available from 1990. At least for this shorter time period using the global factor model does not influence the results significantly.

A key insight of the seminal work by Mitchell and Pulvino [53] is the non linear risk exposure of risk arbitrage returns. Specifically, Mitchell and Pulvino [53] find risk arbitrage returns to have high systematic risk exposure in down markets and a low systematic risk exposure in up markets. To account for the non linear risk exposure I follow Mitchell and Pulvino [53] and run CAPM regressions separately for months with market returns below -4% and above -4%. The results reported in columns 4 and 5 of Table 6 suggest the return spread is stronger during down markets. This is economically intuitive. During down markets there is price pressure due to the de-leveraging of market participants (see e.g. Mitchell and Pulvino [88]). In deals with offer prices above the 52-week high, this price pressure will be stronger as more (leveraged) arbitrageurs are invested in these deals. Although the alphas in down markets are economically larger, they are statistically insignificant. One explanation for the low statistical significance could be the small sample size.

3.5.3 Alternative Explanations

In this section I explore whether other variables, correlated with $\Delta 52$, can explain the predictive power of $\Delta 52$ in the cross-section of risk arbitrage returns.

First, I study whether my results survive after controlling for the offer premium. The offer premium and $\Delta 52$ have a correlation of 0.33, i.e. takeovers with a high value of

[10] The global factors are provided on Kenneth French's homepage http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$\Delta 52$ also have a high offer premium.[11] In the model of Baker and Savasoglu [54] the offer premium is a key determinant of the excess returns in risk arbitrage. A higher offer premium implies a higher loss given default for an arbitrageur and hence, a higher required risk compensation due to an increase in idiosyncratic risk.[12]

Second, I study whether my results survive when I control for the disposition effect. The disposition effect describes the tendency of investors to sell winners and hold on to losers (Shefrin and Statman [81]). In the model of Grinblatt and Han [89], the disposition effect leads to stock price underreaction for winner stocks and stock price overreaction for loser stocks. A takeover announcement is usually good news for investors due to the control premium paid by the acquirer. This holds in particular when the offer price is above the 52-week high as at least all shareholders having acquired the stock in the previous 52-weeks made a positive profit on their investment. Hence, some target shareholder may have a higher propensity to sell their target stocks due to the disposition effect, which could explain my results.

I use cross-sectional regressions of event time returns on $\Delta 52$, the offer premium and a proxy for the disposition effect to test whether the effect of $\Delta 52$ survives. The event time return is defined as the cumulative return in excess of the risk free rate from two days after the announcement until 32 days after the announcement. The 30-day event window ensures that most takeover deals have returns over the full event window (see Baker and Savasoglu [54]).

Table 7 presents the results. In column 1 I only include $\Delta 52$ and consistent with the results from the portfolio sorts, the coefficient is positive and statistically significant. In the regressions I use standardized variables. Hence, the coefficient suggests that a one standard deviation increase in $\Delta 52$ leads to 1% higher event time returns.

[11] The 52-week high is computed as the highest stock price of the target from 385 days before the announcement until 20 days before the announcement. Hence, the offer premium is always higher or equal to $\Delta 52$

[12] As pointed out earlier, Baker and Savasoglu [54] compute the offer premium as the difference between the target stock price 2 days after the announcement and 20 days before the announcement. Merger arbitrage spreads are usually very small however. Therefore, using the difference between the price offered by the acquirer and the target stock price 20 days before the announcement, does not make any difference.

I column 2 of Table 7 I run the regression using only the offer premium. In line with Baker and Savasoglu [54], the offer premium positively predicts risk arbitrage returns. A one standard deviation increase in the offer premium leads to 1.23% higher event time returns. In unreported results I also repeated the portfolio sorts from the previous section replacing $\Delta 52$ with the offer premium. Interestingly, after controlling for systematic risk exposures takeovers with a higher offer premium do not have higher expected returns than takeovers with a low offer premium.

To study the role of the disposition effect, I use the capital gains overhang measure CG of Grinblatt and Han [89]. The capital gains overhang (CG) is computed as $CG = (P_t - R_t)/R_t$. P_t is the closing price at the announcement day and R_t is the market's cost basis defined as

$$R_t = \sum_{n=1}^{\infty} \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n},$$

where V_t is the weekly turnover in a stock at date t and P_t is the stock price. To compute this quantity Grinblatt and Han [89] use weekly data. As it is not feasible to use an infinite sum in the estimation, the authors use as an estimation window a maximum of five years. Column 3 of Table 7 finds that the capital gains overhang does not have any explanatory power for risk arbitrage returns.

Finally, in columns 4 and 5 I study all the three variables together and include other control variables. Columns 4 and 5 find that the effect of $\Delta 52$ stays economically as well as statistically significant after controlling for other variables. Besides the offer premium and the capital gains overhang, I also include the deal attitude (hostile) and the target's market capitalization in the regressions. I include the deal attitude and the target's market capitalization to control for the findings of Baker and Savasoglu [54] that risk arbitrage returns are increasing in completion risk and the target's size.[13]

Overall, the findings from this section suggest that other explanations are not able to explain my results.

[13]Baker and Savasoglu [54] use as a control for completion risk a transformation of the estimated deal success probability. The deal attitude is the most important predictor of deal success however. Hence, I use for simplicity only this variable as a proxy for completion risk. Using more complicated proxies for completion risk does not change my results.

3.5.4 The Role of Arbitrage Capital

Having established a robust unconditional relation between risk arbitrage returns and offer prices above the 52-week high, I study their conditional relation. In particular, I analyze whether the return predictive power of $\Delta 52$ varies systematically with the risk-bearing capacity of the arbitrage sector.

To proxy for the amount of available arbitrage capital, I build on the following idea. It is a well-known fact that mergers and acquisitions occur in cycles (see e.g. Shleifer and Vishny [63]). Figure 1 suggests that in the sample used in this paper there were three waves of M&A activity. There was a merger wave in the 1980s peaking around 1988. The second merger wave occurred at the end of the 1990s and the third merger wave peaked in 2007. If capital is slowly moving into and out of merger arbitrage funds, there will be an oversupply of arbitrage capital in times of low deal activity growth and an undersupply of arbitrage capital in times of high deal activity growth. Such a mechanism can be motivated for example with the work of Pastor and Stambaugh [64]. In their model investors slowly learn and update their beliefs about the returns from active management. Due to this slow updating of beliefs investor capital potentially does not react sufficiently as a response to a changing investment opportunity set.

Drawing on this idea, I hypothesize that at periods when deal activity significantly grows, there is insufficient arbitrage capital to absorb the liquidity demand in takeover deals with offer prices near the target stock's 52-week high. The insufficient amount of arbitrage capital during such times may drive the aforementioned return difference between takeover deals sorted according to $\Delta 52$.

To test this explanation I divide the sample period into states of high deal activity growth, medium deal activity growth and low deal activity growth. The different states are thereby defined in the following way: I compute the percentage deviation of deal volume in USD at the beginning of the month from the average deal volume in the preceding 12 month. I then divide the sample into the three states according to the values of this variable. Table 8 presents the results of the portfolio sorts from section 4.1. separately for states of high deal activity growth and states of low deal activity growth. The lowest tercile portfolio neither generates abnormal returns at times of high deal activity growth nor at times of low deal activity growth. For the highest tercile the results are however significantly different in the two different states. At times of high deal activity growth the portfolio in the highest tercile generate an annual alpha of 10.4% whereas its annual alpha is only 4% at times of low deal activity growth. Hence, slow movement of arbitrage capital across the M&A cycle offers a potential explanation for the persistence of the results documented in the previous sections.

3.6 Additional Results

3.6.1 Transaction costs

This section asks whether the abnormal returns in risk arbitrage documented in the previous section are robust to trading costs. As a first measure I use the Corwin and Schultz [65] spread estimator based on daily high and low prices.[14] This estimator is particularly useful in my sample as in the earlier years bid-ask spreads are often missing especially for stocks outside of the U.S..

As a second measure of transaction costs and I estimate transaction costs using Ancerno trade-level data. Besides paying a spread, investors face price impact costs and direct transaction costs like commissions. Price impact costs have a significant effect on the scalability of investment strategies and are one of the main explanations for the negative relationship between fund size and fund performance in the active management industry.

Keim and Madhavan [66] argue implicit costs like price impact and explicit costs like commissions are not independent from each other. Using the total costs, i.e. the sum of implicit and explicit costs, therefore provides a better estimate of the costs incurred by an investor. As a measure of explicit trading costs I use the trading commissions reported in Ancerno. For the implicit costs I use execution shortfall described in section 2. To get a first impression for the trading costs in takeover deals Figure 4 plots the median transaction costs for different trade complexity groups. I define trade complexity

[14] The estimator is described in more detail in the Appendix.

as the size of the trade compared to the average daily trading volume during the last 20 days. Mitchell and Pulvino [53] conjecture that the trading costs during the takeover deal can be different. Therefore, figure 4 plots the trading costs for the takeover targets before and after the announcement. [15] Figure 4 suggests that indeed the trading costs are different. Specifically, trading for example 10% of average daily trading volume costs 20 basis points in the pre-announcement period and only 10 basis points in the post announcement period which suggests a significant decrease in trading costs during the post-announcement period.

To examine trading costs in more depth, I study trading costs using pooled regressions following Keim and Madhavan [66]. I estimate trading cost functions in three different specifications. The first specification only uses the trade complexity as an independent variable defined as the dollar value of the trade divided by the average daily trading volume during the last 20 days. In the second specification I allow the trade complexity to have a different price impact for buy and sell trades. Finally, in the third specification I use the second specification and add a company's market capitalization as well as a trend variable to control for the declining transaction costs over time. Compared to my analysis in section 3 I use in this section disaggregated data which is significantly more noisy. In order to prevent outliers from driving my results I winsorize the data at the 5% level.

Table 9 shows results separately for targets and acquirers, before and after the acquisition announcement. The after announcement period begins at the second day after announcement to estimate the trading costs.[16] The first column suggests trading 1% of average daily trading volume of a target stock has a price impact of 0.472 basis points and additional costs of 5.542 basis points in the form of spread costs and direct costs. This is a decrease of more than 50% compared to the trading costs in the pre-announcement period shown in Panel A column 4 of Table 9. Panel A column 2 of table 9 suggests there is a small asymmetry in the price impact of buy trades and sell trades, with buy

[15] The post-announcement period is defined as the period from 2 days after the announcement until deal completion. The pre-announcement period is defined as the period from 200 days before the announcement until 2 days before the announcement

[16] The announcement day and the first day after the announcement are excluded from all the estimations

trades being less expensive than sell trades. Finally, in line with Keim and Madhavan [66] trading costs are decreasing in the size of the stock and trading costs are decreasing over time.

Overall, takeover stocks seem to be very liquid. In the model of Kyle [90] the price impact of a trade depends on the uncertainty concerning the value of an asset as well as on the order flow by uninformed investors. On the one hand, I documented significant amounts of uninformed selling due to behavioral effects in section 3. On the other hand, the results of Barber and Odean [91] suggest uninformed buying by investors is increasing when a stock receives a lot of attention in the news or have extreme one day returns. Both of these effects are potential explanations for the significant decrease in trading costs after the takeover announcement.

While it is cheaper to trade takeover stocks in the post-announcement period compared to the pre-announcement period, it becomes more expensive to trade the shares of stock acquirers. Increasing uncertainty concerning the value of the acquirer stock is one explanation for this rise in the trading costs with negative performance consequences for a risk arbitrage strategy as the acquirer stock has to be shorted in a stock deal.

Using the two measures of transaction costs I adjust portfolio returns in order to understand whether the reference price effect is a valuable signal for an arbitrageur after accounting for transaction costs. In practice, except for the short positions in stock acquirers to hedge market risk, risk-arbitrage is a long-only strategy. Thus, to present results from the viewpoint of a risk-arbitrageur I compare after-cost returns for a strategy investing only in takeover deals in the highest tercile of $\Delta 52$ and a strategy investing in a rank-weighted portfolio of all takeover transactions. As a benchmark Panel A of Table 10 presents again results assuming no transaction costs. Panel B of Table 8 shows results using the Corwin and Schultz [65] spread estimator. Accounting for the bid-ask spread decreases average returns as well as alphas by around 1.5% annually for both strategies. Hence, focusing only on the top tercile transactions does not lead to a significant increase in transaction costs which suggests that deals with offer prices near or above the target stock's 52-week high are not less liquid.

In Panels C to G of Table 10 I use the trading cost functions reported in column 3 of Table 9 to simulate the performance of the risk arbitrage portfolios accounting for the price impact of trades. I make three assumptions when simulating the portfolios. First, I assume a cost conscious investor not willing to pay trading costs exceeding 100 basis points. Second, I assume the investor does not want to become a major blockholder. Therefore, I restrict the position size to a maximum of 5% of the outstanding shares of the target company. In times of low deal activity or times with a large number of small transactions these assumptions lead to an increasing fraction of capital invested in cash. I assume the cash account is earning the risk-free rate. Third, I assume the trading cost function estimated for the U.S. is representative for the other countries in my sample. The difference between Panels C to G of Table 10 are the initial portfolio sizes. All the portfolios are simulated for the period from 1985 to 2012, but the initial portfolio size varies from USD 1 million to USD 500 million.

With an initial portfolio size of USD 1 million the transaction costs using the trading costs from Ancerno are lower than the bid-ask spread. According to column 4 of Table 10 the average monthly trading costs are between 11.13 and 12.31 basis point using Corwin and Schultz [65] estimate whereas they are only between 4.56 and 7.29 basis point using the estimates from Ancerno. This is surprising as the second measure of transaction costs even includes commissions whereas we ignore them in the first measure. Apparently, institutional investors are mostly trading inside the bid-ask spread and thus face significantly lower transaction costs.

With an increasing initial portfolio size monthly transaction costs rise to more than 10 basis points and the average fraction of capital invested in takeover deals decreases significantly. For an initial portfolio size of USD 500 million the average fraction of capital invested is only 48% for the strategy investing only in top tercile transactions and 65% for the strategy investing all announced deals. Despite the larger cash position the top tercile strategy however still outperforms. Over the 28 year period it generated an annual excess return (alpha) of 1.75% (0.99%) compared to an annual excess return (alpha) of 1.33% (-0.34%) for the strategy investing in all takeover deals.

3.6.2 An Investment Perspective

This section studies the economic importance of the documented reference price effect from the perspective of a risk-arbitrage arbitrageur taking into account other return predictors in risk arbitrage as well as transaction costs. I therefore employ the parametric portfolio policy approach by Brandt et al. [68]. The Brandt et al. [68] approach is particularly useful in the context of event-driven strategies as it estimates optimal portfolio weights as linear functions of asset characteristics. Hence, it does not require an estimation of returns, variances and covariances, but assumes the joint distribution of returns is fully characterized by the asset characteristics.

In order to account for transaction costs I simulate risk-arbitrage portfolios using either the proportional transaction cost estimate of Corwin and Schultz [65] or non-proportional transaction costs estimated from Ancerno trade-level data.

3.6.2.1 Parametric Portfolio Policies

I assume an investor with power utility and risk aversion $\gamma = 4$.[17] The investor chooses portfolio weights to maximize the conditional expected utility of his portfolio return $r_{p,t}$

$$max_{(w_{i,t})_{i=1}^{N}} E_t[u(r_{p,t})], \tag{3.1}$$

where the portfolio return $r_{p,t}$ is defined as $\sum_{i=1}^{N} w_{i,t} r_{i,t}$. I estimate the weights of the optimal portfolio policy as linear functions of deal characteristics following Brandt et al. [68]. Let x_t be the k-dimensional vector of standardized deal characteristics with mean zero and a standard deviation of one, $\bar{w}_t$ is the weight on all the deals under a benchmark policy. The benchmark policy can be for example an equally weighted portfolio of deals. The linear portfolio policy is then parameterized as

$$w_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta' x_{i,t} \tag{3.2}$$

[17]The power utility function is defined as $U(W) = \frac{W^{(1-\gamma)}}{\gamma}$, where W is the level of wealth

where θ is a k-dimensional vector of parameters to be estimated. The vector θ specifies how an investor should deviate from the benchmark portfolio policy given that a deal characteristic deviates from the cross-sectional mean by one standard deviation. Risk arbitrageurs usually take long positions in takeover situations. Therefore, I impose the short-sale constraint

$$w_{i,t}^{+} = \frac{max[0; w_{i,t}]}{\sum_{i=1}^{N} max[0; w_{i,t}]}. \tag{3.3}$$

In equation (3) the weights are truncated at zero and scaled by the sum of the new weights. The second step ensures that the weights sum up to 1.

To obtain estimates for θ the sample analogue of equations (2) and (3) is maximized,

$$max_{\theta} \frac{1}{T} \sum_{t=1}^{T} u \left(\sum_{i=1}^{N} \frac{max(0; \bar{w}_{i,t} + \frac{1}{N_t}\theta' x_{i,t})}{\sum_{i=1}^{N}(max(0; \bar{w}_{i,t} + \frac{1}{N_t}\theta' x_{i,t})} r_{i,t} \right). \tag{3.4}$$

While equation (4) can be relatively easy maximized it is more difficult to obtain standard errors for the estimated coefficients due to the non-differentiability of w_{it} at zero. The non-differentiability does not allow us to compute the first order derivatives of equation (4) necessary to compute standard errors. This paper therefore uses bootstrapped standard errors instead.

Trading is not costless. When I incorporate transaction costs I change the portfolio return from $w_t' r_t$ to $w_t' r_t - c_t' |w_t - w_{t-1}|$. The vector c_t contains the one-way transaction costs for the different takeover deals.

3.6.2.2 Optimized Portfolios

The approach of Brandt et al. [68] allows to condition the portfolio weights on several variables. Thus, the approach also offers an alternative to test whether other characteristics drive out the cross-sectional importance of the difference between the 52-week high and the offer price. As the benchmark policy I use the rank weights as described in the previous section.[18] Column 1 of Table 11 shows the performance of the rank weighted portfolio. Over the period from 1985 to 2012 portfolio's gross return was 9.7% annually

[18] Using equal weights yields the same results.

with a standard deviation of 6.4%. Even this portfolio has a sharpe ratio of 0.9 which is significantly higher than the sharpe ratio of the market portfolio or the sharpe ratio of other popular investment style like value or momentum. The certainty equivalent return is 8.8% annually. The certainty equivalent is a performance statistics particular useful to assess investment strategies with skewed pay-off profiles like merger arbitrage and for investors caring about moments beyond mean and variance. It is the risk-less pay-off which gives the same utility as the risky profit from the risk arbitrage strategy to a risk-averse investor.

In column 2 of Table 11 I estimate an optimized risk arbitrage portfolio using only the Δ 52 Week High as a conditioning variable. Conditioning on this single variable has a significant effect on the utility of a risk averse investor and also on other commonly used performance statistics. The certainty equivalent increases to 12.2% annually, the sharpe ratio to 1.326 and the CAPM alpha to 7.5% annually. Although the portfolio is more concentrated it is still well diversified. The maximum portfolio weight in a single deal is 8% and on average there is a positive investment in over 50% of the deals. The results from column 2 corroborate the results from the naive portfolio sorts that an investor should tilts its portfolio optimally towards deals where the offer prices exceeds the 52-week high significantly.

In column 3 I add several other conditioning variables. First, I add the size of the deal. As already mentioned,Baker and Savasoglu [54] use size as a proxy for the post-announcement price pressure arbitrageurs have to absorb. Next, I include a stock deal dummy, a tender dummy and a LBO dummy. Mitchell and Pulvino [53] find a higher downside risk exposure of cash deals versus stock deals and attribute this to the financing risk of cash deals. I conjecture that among cash deals the financing risk should be even higher among tender offers and leveraged buyouts. Tender offers are sensitive to adverse movements in the market as they fall under Regulation T. Hence, when the collateral value of the shares is decreasing due to systematic shocks, acquirers can face margin calls with a negative impact on a deal's success probability. Due to the extensive use of leverage, LBOs are in general very sensitive to adverse developments in the equity and credit markets. Thus, if an investor cares about downside risk, he will tilt away from cash financed deals and in particular from tender offers and LBOs. Finally, I include the offer premium measured as the offer price minus the target price before the announcement, the sign of the arbitrage spread at the beginning of the month, a dummy equal to one for hostile deals and a dummy for private acquirers. The economic intuition to include the offer premium and the hostile dummy was already discussed. A negative arbitrage spread suggests that the market expects a positive improvement of the bid. The private acquirer dummy is included due to its high correlation with institutional selling reported in Table 3.

Most of the variables seem to be unimportant from the perspective of a risk averse risk arbitrageur according to the results reported in Table 11 column 3. The only conditioning variables significantly affecting the utility of the investor are Δ 52 Week High, Tender and Arbitrage Spread< 0. The addition of the other conditioning variables improves the performance of the risk arbitrage strategy in the range of 25% to 45% percent. Contrary to the initial conjecture a risk averse investor however optimally tilts his portfolio towards tender offers and not away.

In columns 4 to 6 I incorporate transaction costs into the portfolio decision. As an estimate for the one-way transaction costs I use the Corwin and Schultz [65] spread estimator based on daily high and low prices.[19]This estimator is particularly useful in my sample as in the earlier years bid-ask spreads are often missing especially for stocks outside of the U.S.. Column 5 and 6 suggest transaction costs do not have a strong impact on the parameter estimates of the optimal portfolio policy. The impact on average annual return is similar to Mitchell and Pulvino [53] around 1.5%.[20] Sharpe ratios and alphas decrease by around 30%. Thus, while transaction costs have a significant impact on the performance of the optimized risk arbitrage strategy, it is still a highly profitable strategy.

The results reported in Table 11 are in-sample. Although the risk of over-fitting using the Brandt et al. [68] is significantly smaller compared to other approaches, I estimate the portfolio policy also out-of sample. The 10 year period from 1985 to 1994 is used as

[19]The estimator is described in more detail in the Appendix.

[20]Mitchell and Pulvino [53] report in their Table 7 the impact of indirect transaction costs on a hypothetical fund with assets under management of USD 1 million

the initial estimation period. The coefficients of the initial portfolio policy are then used for the next 12 month, i.e. for 1995. Afterwards, the portfolio policy is re-estimated every year using an expanding window.

In order to see the importance of my key variable $\Delta 52$ for the portfolio policy I plot in figure 3 the estimated parameter for this variable together with the bootstrapped 95% confidence interval. The parameter is slightly increasing over time and the confidence intervals suggest it is always significantly different from zero. Conditioning the portfolio decision on $\Delta 52$ is however not only statistically significant, but also economically. Column 2 of Table 12 suggests an increase of 3.3% in the annual certainty equivalent when an investor conditions his portfolio decision on $\Delta 52$.

Transaction costs have again a significant impact on the performance of the optimized portfolios as well as on the rank-weighted portfolio. On average transaction costs reduce the returns by around 1.5% annually.

3.6.2.3 Are the Profits scalable

I use the trading cost functions reported in column 3 of Table 9 to simulate the performance of optimized risk arbitrage portfolios accounting for the price impact of trades and direct costs like commissions . Again, I make the three assumptions stated in section 4.3.3 when simulating the portfolios. My simulated portfolios are out-of-sample and therefore the trading period is from 1995 to 2012. As a starting value I assume a portfolio of USD 10 million, which is close to the median assets under management (AUM) of a hedge fund at the end of 1994. [21] I compare the optimized risk arbitrage portfolio with price impact to the optimized portfolios without price impact and proportional transaction costs as well as to the non-optimized risk-arbitrage portfolio with price impact.

Figure 5 indicates a substantial influence of the price impact costs on portfolio performance. The optimized portfolio without transaction costs generated an average annual alpha of 8.4% during the sample period and had a sharpe ratio of 1.8. Proportional

[21] An analysis of the Lipper Tass hedge fund database suggests an average AUM of USD 57 million and a median AUM of USD 12 million in December 1994

transaction costs decrease the alpha by 2.2% to 6.2% and the sharpe ratio decreases to 1.3. Finally, incorporating price impact costs leads to an annual alpha of 4.2% and a sharpe ratio of 1.22. While this is a significant performance decrease compared to the no transaction cost case, the optimized portfolio still performs better than the rank-weighted portfolio. Interestingly, using raw returns the performance difference between the optimized and the rank-weighted portfolio is not very large judging from the graph in figure 5. There are however large differences in the alphas and sharpe ratios of the strategies. The optimized strategy has an alpha which is 2.2% per year higher than the alpha of the rank-weighted strategy and the sharpe ratios is also significantly higher (1.22 versus 0.79). In unreported results I find the optimized strategy has a market exposure of only 0.05 compared to a market exposure of 0.2 for the rank-weighted strategy.

Finally, I study how the portfolio performance of the optimized portfolio changes when I vary the initial portfolio size. I start with USD 10 million and increase the initial portfolio size in steps of USD 10 million up to an initial portfolio value of USD 500 million. Figure 6 plots the evolution of annual alphas. The annual alpha decreases in a convex fashion and starting from an initial portfolio size of around USD 200 million the alphas drop below 2. Hence, assuming a hypothetical management fee of 2% the strategy wouldn't have delivered any alpha to investors for an initial portfolio exceeding USD 200 million.

3.7 Conclusion

Prior research suggests that the abnormal returns in risk arbitrage are a compensation for liquidity provision to exiting shareholders. The literature however lacks explanations why this liquidity demand arises in the first place. Our understanding of the abnormal profits in merger arbitrage is therefore incomplete.

This paper provides evidence consistent with a behavioral explanation for the post-announcement liquidity demand and merger arbitrage profits. Importantly, I show that behavioral biases are not only present among retail investor, but also among institutional investors. This implies that the abnormal returns in merger arbitrage may persist despite an increasing institutionalization of equity markets.

A market inefficiency can only persist if there is not enough rational arbitrage capital to correct it. The results of this paper suggest that arbitrage capital reacts too slowly to the strong cyclicality of the M&A market, which lets market inefficiencies persist at least in certain states of the world.

The M&A market is highly discussed in the media and merger arbitrage is a well-known and simple alternative trading strategy. Therefore, to study the causes and the persistence of pricing inefficiencies in this market provides a good starting point to understand inefficiencies in other markets.

Appendix

A.1 Proportional Trading Costs

I use the spread estimator (S) of Corwin and Schultz [65] defined as

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}. \tag{A.1}$$

For a deeper understanding of the estimator the reader should consult the work of Corwin and Schultz [65]. Here, I only state the equations used to compute the estimator.

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \tag{A.2}$$

where

$$\gamma = \left[ln \left(\frac{H^0_{t,t+1}}{L^0_{t,t+1}} \right) \right]^2 \tag{A.3}$$

and

$$\beta = \sum_{j=0}^{1} \left[ln \left(\frac{H^0_{t+j}}{L^0_{t+j}} \right) \right]^2. \tag{A.4}$$

H^0_{t+j} and L^0_{t+j} stand for high and low price on day $t+j$ and $H^0_{t,t+1}$ and $L^0_{t,t+1}$ stand for two day high and low prices in the period from t to $t+1$.

TABLE 3.1: **Summary Statistics Takeover Transactions**

This table presents summary statistics for the sample of takeover transactions from Thomson Financial. The sample starts with all change of control transactions of publicly listed targets in the US, Canada, Australia, New Zealand, Hong Kong, Singapore, Japan, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. For the final sample following filters are applied (1) In the US I only keep deals where I am able match the cusip of the target provided by SDC with the CRSP daily tapes. For all other countries I require a valid match between a target's cusip (Canada), sedol (rest of the world) or name with the Compustat Global Security Daily files. For equity financed deals I furthermore require a valid match between the acquirer's cusip, sedol or name and CRSP or Compustat, (2) A deal has to be pure cash or pure stock financed. For stock financed deals I require a valid exchange ratio from SDC; (3) deals with negative bid premia, initial arbitrage spreads of more than 100% or smaller than -20% are deleted; (4) deals with a value of less than USD 10 million are deleted. The "Offer Premium" is defined as the difference between the offer price and the target stock price 20 days prior to announcement scaled by the target stock price 20 days prior to announcement. "Δ 52" is defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high. "Target Size" is the target's market capitalization in USD billions. All the other variables are dummies

	Obs	**Mean**	**Std. Dev.**	**25th Pct.**	**Median**	**75th Pct.**
	Panel A: International					
Offer Premium	7740	0.395	0.308	0.187	0.333	0.530
Δ 52 Week High	7740	0.025	0.301	-0.130	0.032	0.198
Target size	7740	0.711	2.822	0.0440	0.125	0.418
Tender	7740	0.448	0.497	0	0	1
Stock	7740	0.201	0.401	0	0	0
Hostile	7740	0.0610	0.239	0	0	0
LBO	7740	0.135	0.341	0	0	0
Private	7740	0.43	0.49	0	0	1
Completed	7740	0.750	0.433	0	1	1
	Panel B: US					
Offer Premium	4888	0.424	0.313	0.209	0.360	0.563
Δ 52 Week High	4888	0.063	0.310	-0.111	0.085	0.247
Target size	4888	0.723	2.989	0.0452	0.130	0.431
Tender	4888	0.320	0.467	0	0	1
Stock	4888	0.215	0.411	0	0	0
Hostile	4888	0.0620	0.241	0	0	0
LBO	4888	0.139	0.346	0	0	0
Private	4888	0.38	0.49	0	0	1
Completed	4888	0.796	0.403	1	1	1
	Panel C: International ex US					
Offer Premium	2852	0.346	0.293	0.154	0.284	0.474
Δ 52 Week High	2852	-0.040	0.273	-0.149	0.004	0.103
Target size	2852	0.689	2.499	0.0426	0.117	0.401
Tender	2852	0.667	0.471	0	1	1
Stock	2852	0.176	0.381	0	0	0
Hostile	2852	0.0593	0.236	0	0	0
LBO	2852	0.128	0.334	0	0	0
Private	2852	0.51	0.50	0	1	1
Completed	2852	0.670	0.470	0	1	1

TABLE 3.2: **Summary Statistics Ancerno**

This table shows summary statistics for the matched sample of US takeover transactions and trade level data provided by Ancerno. Panel A shows summary statistics for the takeover targets. Panel A to Panel C provide trading statistics for target stocks for the full sample, before the takeover announcement and after the takeover announcement. "Managers" is the number of managers in the Ancerno database trading the target stock. "Price Impact" is execution shortfall (ES) defined as $ES(t) = \frac{P_l(t)-P_0(t)}{P_0(t)}D(t)$, where $P_l(t)$ is the average execution price, $P_0(t)$ is the prior day's closing price and $D(t)$ is the direction of the trade. Commisions per stock traded are expressed as a fraction of prior day's closing pricing. Total costs are commissions plus price impact and trade size is expressed in thousand dollars.

	Obs	**Mean**	**Stdev.**	**25th Pct.**	**Median**	**75th Pct.**
	Panel A: Deal Characteristics - Ancerno Match					
Offer Premium	1601	0.43	0.33	0.21	0.36	0.58
Δ 52 Week High	1601	0.02	0.32	-0.16	0.05	0.20
Target Size	1601	0.99	3.25	0.07	0.21	0.70
Tender	1601	0.27	0.45	0	0	1
Stockdeal	1601	0.19	0.40	0	0	0
Hostile	1601	0.02	0.13	0	0	0
LBO	1601	0.14	0.35	0	0	0
Private	1601	0.28	0.45	0	0	1
Completed	1601	0.86	0.35	1	1	1
	Panel B: Full Sample - Trading Statistics					
Managers	1601	25.25	27.26	4.00	15.00	38.00
Price Impact	1601	0.03	2.19	-0.82	0	0.88
Commisions	1601	0.10	1.76	0.02	0.05	0.12
Total Cost	1601	0.13	2.81	-0.73	0.09	0.98
Trade Size	1601	1214	7120	15.42	77.21	418.20
	Panel C: Before Announcement- Trading Statistics					
Managers	1601	22.43	23.79	4.00	14.00	34.00
Price Impact	1601	0.04	2.28	-0.95	0	1.02
Commisions	1601	0.11	2.16	0.02	0.06	0.13
Total Cost	1601	0.14	3.14	-0.86	0.11	1.12
Trade Size	1601	1038	5887	13.93	68.63	363.50
	Panel D: After Announcment - Trading Statistics					
Managers	1601	16.53	19.19	3.00	9.00	24.00
Price Impact	1601	0.02	2.04	-0.62	0	0.66
Commisions	1601	0.09	0.79	0.01	0.05	0.11
Total Cost	1601	0.11	2.19	-0.54	0.07	0.75
Trade Size	1601	1494	8713	18.22	93.74	519.50

TABLE 3.3: **Institutional Trading around Takeover Announcements**

This table shows regressions of net trading of institutional investors around takeover announcement. The dependent variable is defined as the sum all trades from the announcement today until the 10th day after the announcement as a percentage of total shares outstanding."Offer Premium" is defined as the difference between the offer price and the target stock price 20 days prior to announcement scaled by the target stock price 20 days prior to announcement. In all specifications labeled "continuous" the variable "Δ 52" is defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high. In all specifications labeled "dummy" the variable "Δ 52" is equal to 1 if the offer price exceeds the target's 52-week high. "Size" is the log of the target's market capitalization. All the other variables are dummies.*,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	Dummy	**Dummy**	**Continuous**	**Continuous**	**Dummy**	**Dummy**	**Continuous**	**Continuous**
Δ52 Week High	-0.80***	-0.44***	-1.07***	-0.70***	-0.63***	-0.32**	-0.92***	-0.55**
	(-5.48)	(-3.12)	(-4.79)	(-3.17)	(-4.35)	(-2.27)	(-4.14)	(-2.48)
Offer Premium		0.10		0.22		-0.27		-0.17
		(0.46)		(1.03)		(-1.31)		(-0.78)
Stockdeal		1.38***		1.37***		0.75***		0.74***
		(7.06)		(7.01)		(3.71)		(3.65)
Size		-0.53***		-0.53***		-0.50***		-0.50***
		(-10.85)		(-10.80)		(-10.31)		(-10.23)
Tender		-0.17		-0.21		-0.60***		-0.64***
		(-1.02)		(-1.25)		(-3.59)		(-3.77)
Private		0.85***		0.85***		0.86***		0.86***
		(3.96)		(3.98)		(4.09)		(4.10)
LBO		-0.20		-0.19		-0.21		-0.20
		(-0.76)		(-0.74)		(-0.82)		(-0.81)
Hostile		-0.09		-0.02		-0.28		-0.24
		(-0.18)		(-0.05)		(-0.59)		(-0.51)
Constant	-1.52***	4.51***	-1.96***	4.20***	-1.62***	4.50***	-1.97***	4.25***
	(-13.58)	(6.91)	(-27.12)	(6.32)	(-14.83)	(6.93)	(-28.30)	(6.44)
Time Fixed Effects	N	N	N	N	Y	Y	Y	Y
Observations	1,322	1,322	1,322	1,322	1,322	1,322	1,322	1,322
R-squared	0.02	0.15	0.02	0.15	0.10	0.21	0.10	0.21

TABLE 3.4: **The 52 Week High and Risk Arbitrage Returns**

At the beginning of each month all announced takeover transactions are sorted into three size rank weighted portfolios according to Δ52, defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high. Monthly excess returns of the portfolios are regressed on the market factor (MKTRF), the small minus big factor (SMB) and the high minus low factor (HML) of Fama and French [32] factors as well as on momentum factor (UMD) of Carhart [15]. High-Low is a long-short portfolio going long the portfolio with takeover stocks in the highest Δ52 tercile and short the takeover stocks in the lowest Δ52 tercile. *,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	Low	**Medium**	**High**	**High - Low**
Panel A: US(1985-2012)				
Excess Return (in % per year)	3.67	4.00	8.84	4.98
Sharpe Ratio	0.35	0.51	1.00	0.41
MKTRF	0.33***	0.26***	0.18***	-0.14***
	(9.70)	(10.21)	(6.53)	(-3.37)
SMB	0.14***	0.07*	0.15***	0.01
	(3.00)	(1.90)	(3.89)	(0.19)
HML	0.15***	0.13***	0.11**	-0.04
	(2.89)	(3.29)	(2.51)	(-0.64)
UMD	-0.01	-0.01	-0.04	-0.03
	(-0.17)	(-0.41)	(-1.52)	(-0.86)
Alpha (in % per month)	0.05	0.14	0.58***	0.53***
	(0.34)	(1.29)	(4.76)	(2.85)
Observations	336	336	336	336
R-squared	0.27	0.27	0.19	0.03
Panel B: International (1985-2012)				
Excess Return (in % per year)	3.31	4.32	8.83	5.36
Sharpe Ratio	0.33	0.57	1.23	0.57
Alpha (in % per month)	0.00	0.14	0.60***	0.59***
	(0.03)	(1.32)	(5.67)	(3.99)
Panel C: International excluding the US (1999-2012)				
Excess Return (in % per year)	0.71	4.80	7.39	6.64
Sharpe Ratio	0.06	0.51	0.63	0.45
Alpha (in % per month)	-0.06	0.35*	0.56**	0.62*
	(-0.24)	(1.74)	(2.09)	(1.88)

TABLE 3.5: **Different Portfolio Return Aggregation Schemes**

At the beginning of each month all announced takeover transactions are sorted into three size rank weighted portfolios according to Δ52, defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high. Monthly excess returns of the portfolios are regressed on the market factor (MKTRF), the small minus big factor (SMB) and the high minus low factor (HML) of Fama and French [32] factors as well as on momentum factor (UMD) of Carhart [15]. High-Low is a long-short portfolio going long the portfolio with takeover stocks in the highest Δ52 tercile and short the takeover stocks in the lowest Δ52 tercile. *,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	Daily Returns				**Value-weighted Returns**			
	Low	**Medium**	**High**	**High - Low**	**Low**	**Medium**	**High**	**High - Low**
Excess Return (in % per year)	5.17	7.63	13.70	7.90	7.37	5.63	9.48	1.97
Sharpe Ratio	0.47	0.89	1.63	0.74	0.40	0.49	0.84	0.10
MKTRF	0.33***	0.28***	0.18***	-0.16***	0.70***	0.33***	0.17***	-0.52***
	(9.47)	(9.95)	(6.18)	(-4.00)	(12.20)	(8.85)	(4.22)	(-7.48)
SMB	0.19***	0.09**	0.16***	-0.03	-0.10	0.14***	0.08	0.18*
	(3.77)	(2.18)	(3.97)	(-0.50)	(-1.23)	(2.72)	(1.44)	(1.85)
HML	0.18***	0.13***	0.12***	-0.06	0.25***	0.27***	0.11*	-0.14
	(3.27)	(3.02)	(2.65)	(-0.98)	(2.91)	(4.66)	(1.76)	(-1.34)
UMD	-0.04	0.05*	-0.03	0.02	-0.01	-0.02	-0.04	-0.03
	(-1.36)	(1.89)	(-1.15)	(0.44)	(-0.16)	(-0.53)	(-0.98)	(-0.45)
Alpha (in % per month)	0.18	0.38***	0.94***	0.74***	0.12	0.18	0.64***	0.52*
	(1.17)	(3.11)	(7.49)	(4.37)	(0.47)	(1.10)	(3.57)	(1.72)
Observations	336	336	336	336	336	336	336	336
R-squared	0.28	0.26	0.17	0.06	0.32	0.24	0.07	0.15

TABLE 3.6: **The Role of Risk**

At the beginning of each month all announced takeover transactions are sorted into three rank weighted portfolios according to $\Delta 52$, defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high. The table reports results for regressions of the portfolios' monthly excess returns on different risk-factors. MKTRF, SMB, HML are the Fama and French [32] factors, UMD is the momentum factor of Carhart [15], LMP is the leverage mimicking factor of Adrian et al. [45] and PS is the traded liquidity risk factor of Pastor and Stambaugh [33]. Column 3 uses the global versions of the Fama and French [32] and Carhart [15] factors. In column 4 a down market is defined as a contemporaneous market return below -4%. In column 5 an up market is defined as a contemporaneous market return above -4%. *,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	LMP	**PS**	**Global Factors**	**Down Market**	**Up Market**
MKTRF	-0.24***	-0.18***	-0.13***	-0.16	-0.14***
	(-3.71)	(-4.77)	(-3.55)	(-1.27)	(-3.05)
SMB	-0.01	-0.01	-0.03		
	(-0.24)	(-0.10)	(-0.41)		
HML	-0.19	-0.07	-0.11		
	(-1.58)	(-1.20)	(-1.57)		
UMD	-0.12*	-0.05	-0.01		
	(-1.75)	(-1.47)	(-0.60)		
LMP	0.15				
	(1.19)				
PS		-0.04			
		(-1.06)			
Alpha	0.58***	0.63***	0.53***	0.73	0.48***
	(3.61)	(3.89)	(3.16)	(0.71)	(2.71)
Observations	306	306	240	46	290
R-squared	0.08	0.07	0.06	0.04	0.03

Table 3.7: **Alternative Explanations**

This table shows OLS regressions of 30 day excess even returns on Δ52, defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high, and a number of control variables. Offer Premium is defined as the difference between the offer price and the target stock price 20 days prior to announcement scaled by the target stock price 20 days prior to announcement; CG is the capital gains overhang measure of Grinblatt and Han [89], Size is the log market capitalization of the target, hostile and stockdeal are dummies equal to 1 for an unfriendly takeover offer and payment in stock, respectively. T-statistics are in parentheses and all standard are clustered at the monthly level. *,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	(1)	(2)	(3)	(4)	(5)
Δ52	1.01***			0.72***	0.66***
	(5.61)			(3.92)	(3.43)
Offer Premium		1.24***		1.01***	0.98***
		(6.86)		(5.53)	(4.97)
CG			0.03	-0.17	-0.27
			(0.17)	(-1.14)	(-1.62)
Size					-0.21
					(-1.56)
Hostile					3.03***
					(4.40)
Stockdeal					-0.85**
					(-2.49)
Constant	1.18***	1.18***	1.18***	1.18***	1.19***
	(8.29)	(8.24)	(8.22)	(8.33)	(6.77)
Observations	7,831	7,831	7,831	7,831	7,732
R-squared	0.01	0.01	0.00	0.02	0.02

TABLE 3.8: **Time-varying arbitrage capital**

This table presents results for portfolios sorted on $\Delta 52$, defined as the difference between the offer price and the target stock's 52-week high scaled by the target stock 52-week high. The High-Low portfolio is a long-short portfolio going long the portfolio with takeover stocks in the highest $\Delta 52$ tercile and short the takeover stocks in the lowest $\Delta 52$ tercile. Column 1-4 show results for states with high deal activity growth. Column 5-8 show results for states with low deal activity growth.The different states are thereby defined in the following way: I compute the percentage deviation of deal volume in USD at the beginning of the month from the average deal volume in the preceding 12 month. I then divide the sample into three terciles according to the values of this variable. The highest tercile defines the state with high deal activity growth whereas the lowest tercile defines the low activity state. MKTRF, SMB, HML are Fama and French [32] factors, UMD is the momentum factor of Carhart [15]. *,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	High Deal Activity Growth				**Low Deal Activity Growth**			
	Low	**Medium**	**High**	**High - Low**	**Low**	**Medium**	**High**	**High - Low**
Mean Excess Return (in % per year)	4.17	5.89	10.55	6.15	3.53	1.90	6.31	2.69
Sharpe Ratio	0.69	1.15	1.98	0.83	0.29	0.24	0.80	0.22
MKTRF	0.20***	0.14***	0.06	-0.14**	0.32***	0.24***	0.18***	-0.14*
	(4.49)	(3.69)	(1.44)	(-2.37)	(4.61)	(5.21)	(3.88)	(-1.83)
SMB	0.08	0.12**	0.10	0.02	0.21**	0.01	0.11*	-0.10
	(1.18)	(2.11)	(1.53)	(0.20)	(2.12)	(0.20)	(1.68)	(-0.91)
HML	0.12*	0.13**	-0.00	-0.13	0.13	0.12**	0.11*	-0.02
	(1.74)	(2.14)	(-0.07)	(-1.37)	(1.46)	(2.10)	(1.90)	(-0.18)
UMD	0.02	0.05	-0.02	-0.04	0.00	0.01	-0.04	-0.04
	(0.45)	(1.26)	(-0.50)	(-0.70)	(0.01)	(0.23)	(-1.18)	(-0.69)
Alpha	0.21	0.37**	0.83***	0.62***	-0.01	-0.02	0.32	0.33
	(1.29)	(2.62)	(5.29)	(2.82)	(-0.03)	(-0.09)	(1.62)	(0.97)
Observations	108	108	108	108	110	110	110	110
R-squared	0.18	0.17	0.06	0.06	0.27	0.25	0.25	0.05

Table 3.9: **Transaction Costs**

This table shows estimates of transaction costs in takeover stocks. The dependent variable is the total transaction cost defined as the sum of execution shortfall and commissions as a fraction of the share price in basis points. Execution shortfall is defined as $ES(t) = \frac{P_l(t)-P_0(t)}{P_0(t)}D(t)$, where $P_l(t)$ is the average execution price, $P_0(t)$ is the prior day's closing price and $D(t)$ is the direction of the trade. Size is the natural logarithm of a stock's market capitalization in thousand. Trend is defined as (Year-1999). Complexity is the dollar volume of a trade divided by the average daily trading volume of the stock during the previous 20 days. Buy is a dummy equal to one for buy trades. Sell is a dummy equal to one for sell trades. In order to prevent outliers to drive the results all the regressions are estimated using robust regression techniques. *,**,*** denotes statistical significance at the 10%, 5% and 1% significance level respectively.

	Trading Costs in Target Stocks					
	After Announcement			**Before Announcement**		
Buy*Complexity		0.483***	0.377***		1.004***	0.937***
		(3.571)	(2.714)		(10.34)	(9.366)
Sell*Complexity		0.468***	0.389***		1.255***	1.195***
		(5.077)	(4.102)		(12.39)	(11.54)
Trend			-0.0402			-0.238*
			(-0.330)			(-1.799)
Size (in logs)			-0.893***			-0.628**
			(-3.764)			(-2.345)
Complexity	0.472***			1.124***		
	(5.957)			(15.14)		
Intercept	5.547***	5.546***	19.22***	7.881***	7.882***	18.59***
	(14.38)	(14.38)	(5.181)	(18.90)	(18.91)	(4.589)
Observations	103,060	103,060	103,060	223,967	223,967	223,967
R-squared	0.000	0.000	0.000	0.001	0.001	0.001
	Trading Costs in Stock Acquirers					
Buy*Complexity		1.273***	1.350***		1.114***	1.130***
		(5.063)	(5.214)		(4.706)	(4.638)
Sell*Complexity		1.811***	1.892***		1.638***	1.653***
		(5.915)	(6.066)		(6.414)	(6.359)
Trend			-0.133			0.157
			(-0.558)			(0.804)
Size (in logs)			0.625			0.0456
			(1.582)			(0.133)
Complexity	1.486***			1.354***		
	(7.386)			(7.526)		
Intercept	8.007***	7.994***	-2.081	6.813***	6.813***	5.358
	(10.31)	(10.30)	(-0.299)	(9.917)	(9.917)	(0.884)
Observations	66,220	66,220	66,220	91,085	91,085	91,085
R-squared	0.001	0.001	0.001	0.001	0.001	0.001

TABLE 3.10: **Portfolio Returns after Transaction Costs**

This table presents the performance of different trading strategies in risk arbitrage after transaction costs in the period from 1985-2012. The strategy "Top Tercile Transactions" invests in a rank-weighted portfolio of takeover transactions in the highest $\Delta 52$ tercile. The strategy "All Takeover Transactions" invests in a rank-weighted portfolio of all takeover transactions. Panel A assumes no transaction costs and Panel B uses the bid-ask spread estimator of Corwin and Schultz [65] to compute net-of-cost returns. Panels C-G use the transaction cost functions estimated from Ancerno trade-level data reported in Column 3 of Table 7 to adjust portfolio returns. When simulating the portfolio returns in Panels C-G the following assumptions are made: First, I assume a cost conscious investor not willing to pay trading costs exceeding 100 basis points. Second, I assume the investor does not want to become a major blockholder. Therefore, I restrict the position size to a maximum of 5% of the outstanding shares of the target company. At times of low deal activity or times with a large number of small transactions these assumptions lead to an increasing fraction of capital invested in cash. I assume the cash account is earning the risk-free rate. Third, I assume the trading cost function estimated for the U.S. is representative for the other countries in my sample.

	Alpha in % per year	**Sharpe Ratio**	**Excess Return in % per year**	**Trading Costs in Bps per month**	**Average Fraction Invested**
	Panel A: No Transaction Costs				
Top Tercile Transactions	6.84	1.20	8.40	0	1.00
All Takeover Transactions	3.09	0.87	5.55	0	1.00
	Panel B: Bid-Ask Spread Estimator				
Top Tercile Transactions	5.16	0.96	6.66	11.13	1.00
All Takeover Transactions	1.42	0.61	3.85	12.31	1.00
	Panel C: Ancerno Transaction Cost Function - initial portfolio size: USD 1 million				
Top Tercile Transactions	5.58	1.04	7.16	7.29	0.99
All Takeover Transactions	2.30	0.76	4.78	4.56	1.00
	Panel D: Ancerno Transaction Cost Function -initial portfolio size: USD 10 million				
Top Tercile Transactions	4.41	0.88	5.90	13.53	0.93
All Takeover Transactions	1.58	0.65	4.07	8.88	0.97
	Panel E: Ancerno Transaction Cost Function - initial portfolio size: USD 50 million				
Top Tercile Transactions	3.03	0.75	4.39	15.83	0.80
All Takeover Transactions	0.57	0.51	2.98	13.36	0.91
	Panel F: Ancerno Transaction Cost Function - initial portfolio size: USD 100 million				
Top Tercile Transactions	2.14	0.63	3.36	15.57	0.73
All Takeover Transactions	0.24	0.45	2.46	14.71	0.85
	Panel G: Ancerno Transaction Cost Function - initial portfolio size: USD 500 million				
Top Tercile Transactions	0.99	0.47	1.75	11.82	0.48
All Takeover Transactions	-0.34	0.31	1.33	14.29	0.65

Table 3.11: **In-Sample Results**

Long-only optimal portfolio policy parameters are estimated for all cash and stock deals over the 1985-2012 sample period for different specifications: (I) corresponds to a size ranked merger arbitrage portfolio; (II) uses only Δ52 as a conditioning variable; (III) adds the offer premium, the log target size and dummies for stock deals, tender offers, LBOs, private acquirers and hostile transactions. In the optimization, the risk aversion parameter is set to 4. The first set of rows shows the estimated parameters of the portfolio policy and their associated standard errors. The standard errors are estimated using the bootstrap and statistically significant parameters are in bold. The second set of rows displays the certainty-equivalent return, the average return, standard deviation of return, the sharpe ratio, the CAPM alpha and the four factor alpha.All the statistics are annualized. The third set of rows shows the average absolute portfolio weight, the minimum and maximum portfolio weight, the average sum of negative weights in the portfolio and the average fraction of negative weights in the portfolio. Columns 1 to 3 show results without transactions and columns 4 to 6 show results including proportional transaction costs. Proportional transaction costs are estimated using the Corwin and Schultz [65] bid-ask spread estimator.

	Excluding Transaction Costs			**Including Transaction Costs**		
	Rank		**Optimized**	**Rank**		**Optimized**
	I	II	III	I	II	III
$\theta_{\Delta 52}$		**4.50**	**3.42**		**4.40**	**3.87**
		1.34	*1.77*		*1.45*	*1.36*
θ_{SIZE}			-3.12			-2.55
			1.56			*1.29*
$\theta_{STOCKDEAL}$			2.64			1.00
			2.10			*1.22*
θ_{TENDER}			**5.19**			**4.56**
			1.90			*1.56*
θ_{LBO}			-1.00			-1.90
			1.22			*1.12*
$\theta_{OFFERPREMIUM}$			-0.19			0.37
			1.69			*1.37*
$\theta_{SPREAD<0}$			**-5.66**			**-4.92**
			1.36			*1.17*
$\theta_{HOSTILE}$			-1.87			-1.12
			2.34			*1.85*
$\theta_{PRIVATE}$			1.06			0.91
			1.68			*1.31*
CE	0.088	0.122	0.150	0.071	0.104	0.118
Mean Return	0.097	0.133	0.159	0.080	0.115	0.128
Stdev	0.064	0.070	0.064	0.064	0.070	0.065
Sharpe Ratio	0.905	1.326	1.884	0.638	1.074	1.360
α_{CAPM}(per year)	0.037	0.075	0.109	0.021	0.059	0.077
α_{FF4} (per year)	0.031	0.072	0.107	0.015	0.056	0.076
$\lvert w_t \rvert$	0.01	0.01	0.01	0.015	0.015	0.015
min	0.00053	0	0	0.001	0.000	0.000
max	0.03	0.08	0.07	0.029	0.075	0.077
$\sum w\_tI(w\_t < 0)$	0	0	0	0.000	0.000	0.000
$\sum I(w\_t \leq 0)$	0	0.39	0.41	0.000	0.385	0.423

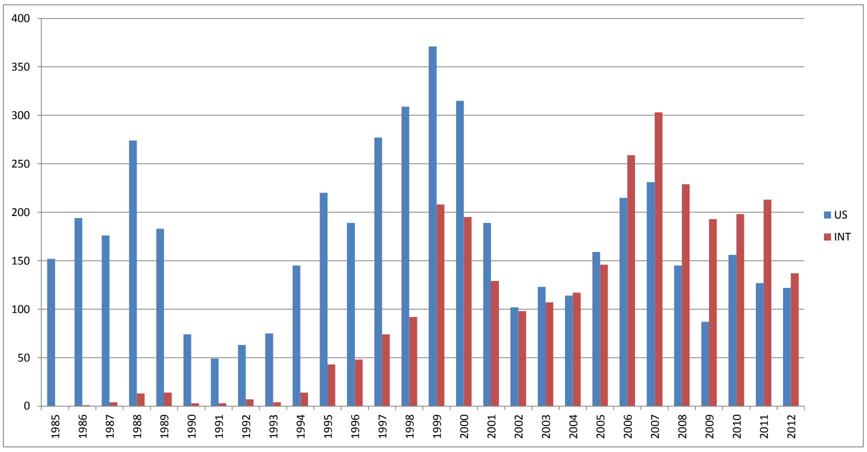
TABLE 3.12: **Out-of-Sample Results**

In the out-of-sample results, I use data until December 1994 to estimate the parameters of the long-only portfolio policy and then form out-of-sample portfolios using those parameters in the next year. Every subsequent year, the portfolio policy is reestimated using the enlarged sample. Results for the out-of-sample period from 1995 to 2012 are reported for different specifications: (I) corresponds to a size ranked merger arbitrage portfolio; (II) uses only Δ52 as a conditioning variable; (III) adds the offer premium, the log target size and dummies for stock deals, tender offers, LBOs, private acquirers and hostile transactions. In the optimization, the risk aversion parameter is set to 4. The first set of rows displays the certainty-equivalent return, the average return, standard deviation of return, the sharpe ratio, the CAPM alpha and the four factor alpha.All the statistics are annualized. The third set of rows shows the average absolute portfolio weight, the minimum and maximum portfolio weight, the average sum of negative weights in the portfolio and the average fraction of negative weights in the portfolio. Columns 1 to 3 show results without transactions and columns 4 to 6 show results including proportional transaction costs. Proportional transaction costs are estimated using the Corwin and Schultz [65] bid-ask spread estimator.

	Excluding Transaction Costs			**Including Transaction Costs**		
	Rank weighted	**Optimized**		**Rank weighted**	**Optimized**	
	I	II	III	I	II	II
CE	0.077	0.110	0.116	0.061	0.095	0.094
Mean Return	0.083	0.116	0.123	0.067	0.101	0.100
Stdev	0.052	0.053	0.055	0.052	0.053	0.055
Sharpe Ratio	1.022	1.645	1.702	0.717	1.360	1.298
α_{CAPM} (per year)	0.037	0.075	0.084	0.022	0.061	0.062
α_{FF4} (per year)	0.033	0.073	0.084	0.018	0.058	0.062
$\|w_t\|$	0.015	0.012	0.012	0.015	0.012	0.012
min	0.001	0.000	0.000	0.001	0.000	0.000
max	0.029	0.067	0.066	0.029	0.067	0.065
$\sum w_t I(w\_t < 0)$	0.000	0.000	0.000	0.000	0.000	0.000
$\sum I(w_t \leq 0)$	0.000	0.385	0.408	0.000	0.383	0.403

FIGURE 3.1: **Takeover Activity**

The top graph shows the annual number of takeover transactions in the US and in an international sample excluding the US. The bottom graph shows the annual dollar volume in USD billions of takeover transactions in the US and in an international sample excluding the US.



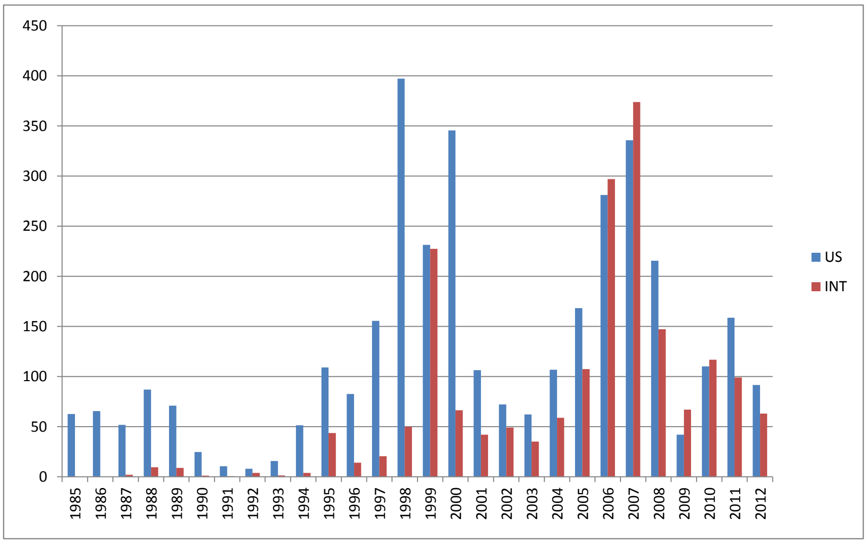
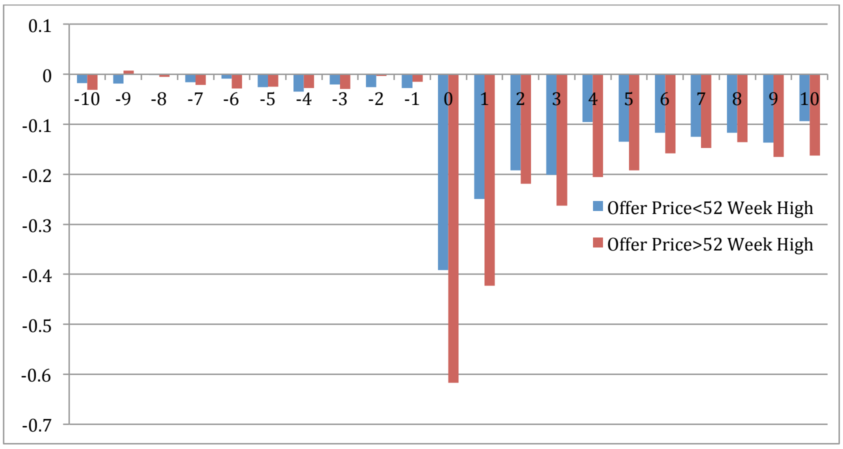


FIGURE 3.2: **Net trading volume around takeover announcements**

The top graph shows the average aggregate net trading volume of institutional investors as a fraction of total shares outstanding around takeover announcements (in %) separately for deals with offer prices above the 52-week high and deals with offer prices below the 52-week high. The bottom graph shows the median aggregate net trading volume of institutional investors as a fraction of total shares outstanding around takeover announcements (in %) separately for deals with offer prices above the 52-week high and deals with offer prices below the 52-week high.



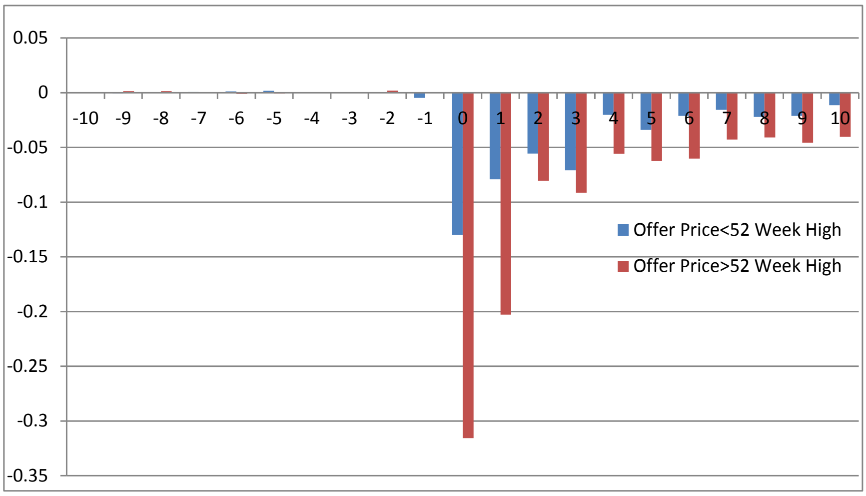


FIGURE 3.3: **Confidence Interval**

The solid line shows the annual parameter $\theta_{\Delta 52}$ for an optimal long-only parametric portfolio policy using only $\Delta 52$ as a conditioning variable. The portfolio policy is estimated using an expanding window beginning in December 1994 and ending in December 2011. The dashed lines show the 95% bootstrapped confidence interval.

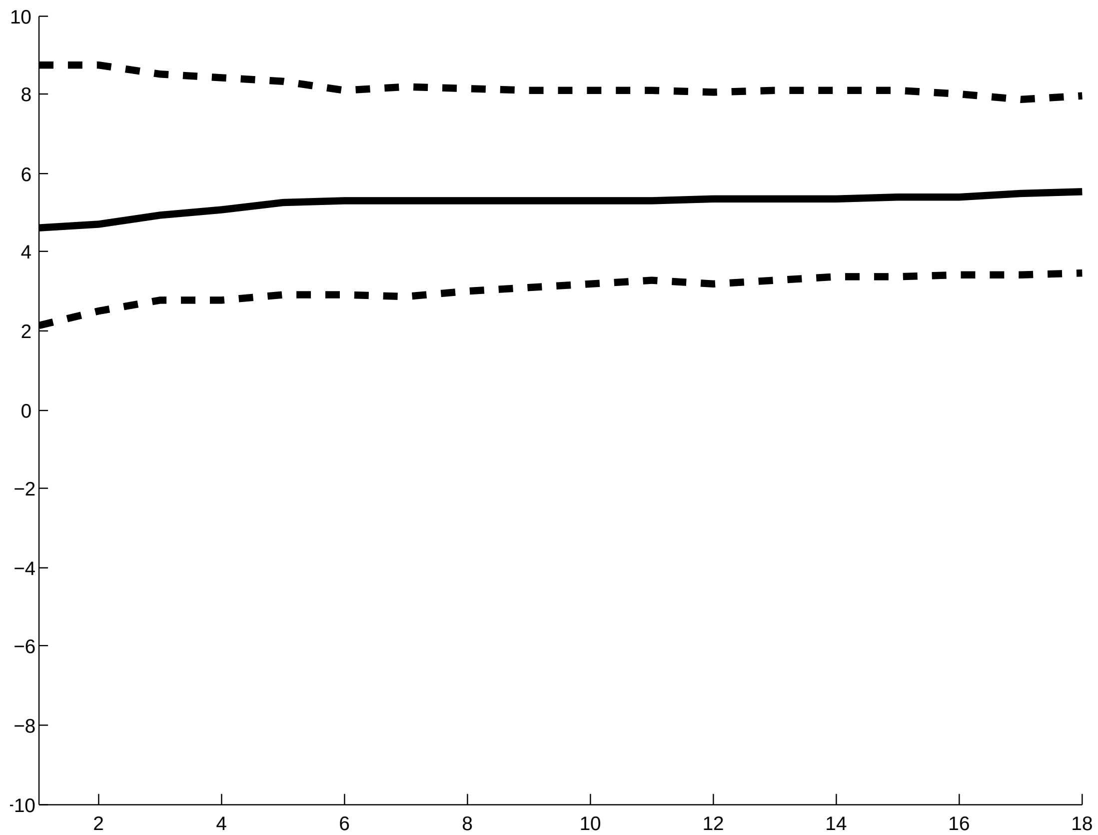


FIGURE 3.4: **Trading Cost**

This graph plots the median trading costs for takeover targets before and after the takeover announcement for different trade sizes. I divide all institutional transaction into 20 bins according their complexity. Complexity is defined as trade size divided by average daily trading volume in the previous 20 days. The y-axis plots median trading costs in basis point. The x-axis shows the median complexity in % of average daily trading volume for each bin.

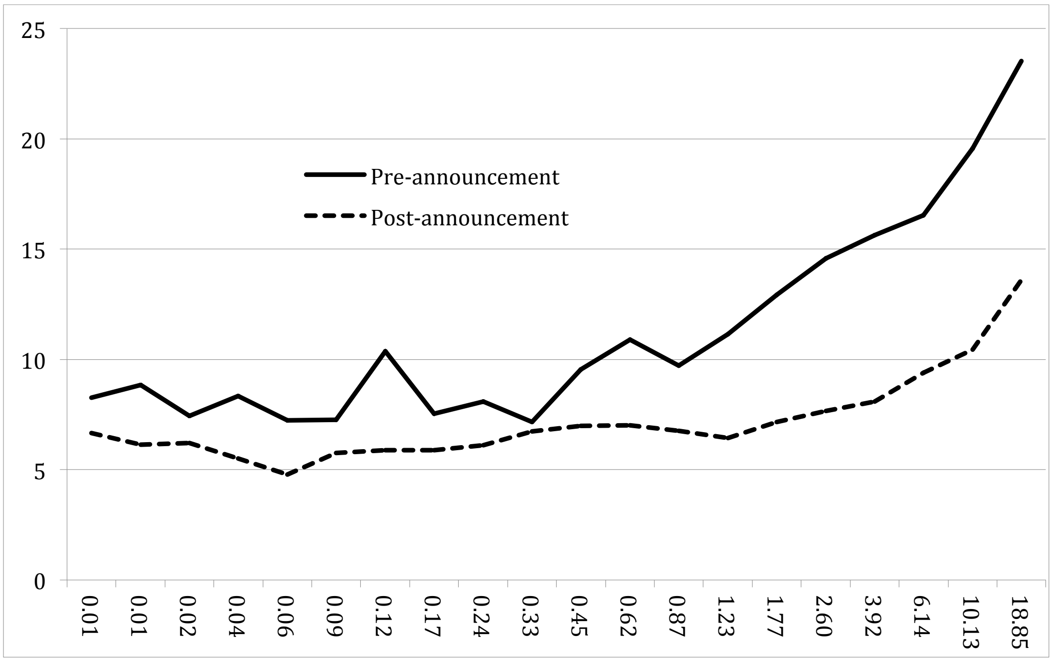


FIGURE 3.5: **Out-of-Sample Returns in Risk Arbitrage**

This graph shows the performance of different risk arbitrage portfolios. All the optimized portfolios are estimated out-of-sample using all eight deal characteristics shown in Table 7. The sample period runs from January 1995 to December 2012. The portfolios adjusted for non-proportional transaction costs have an initial portfolio size of USD 10 million and the used transaction cost functions are displayed in table 9 column 3.

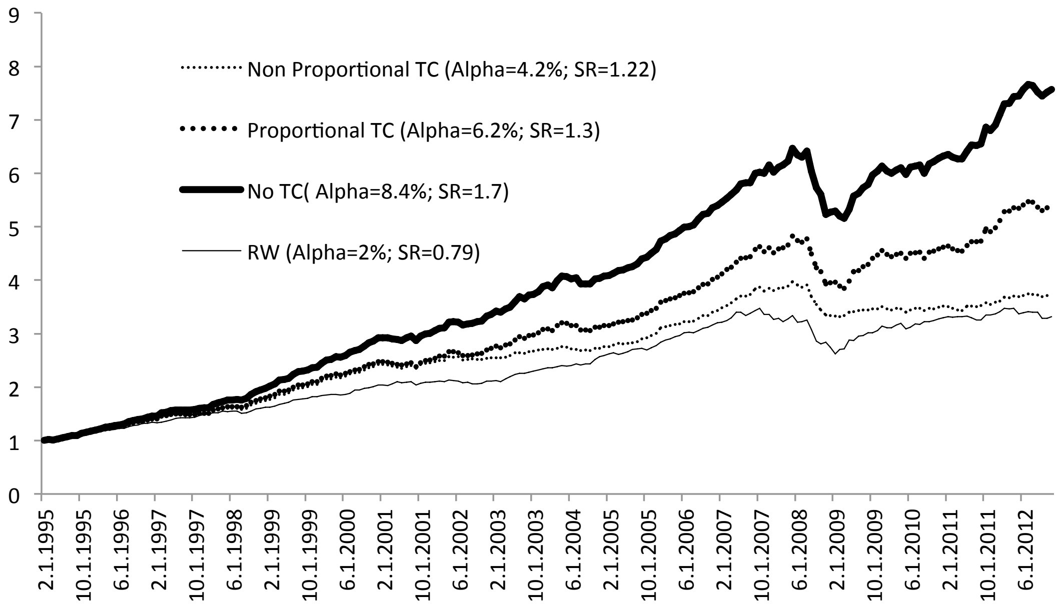
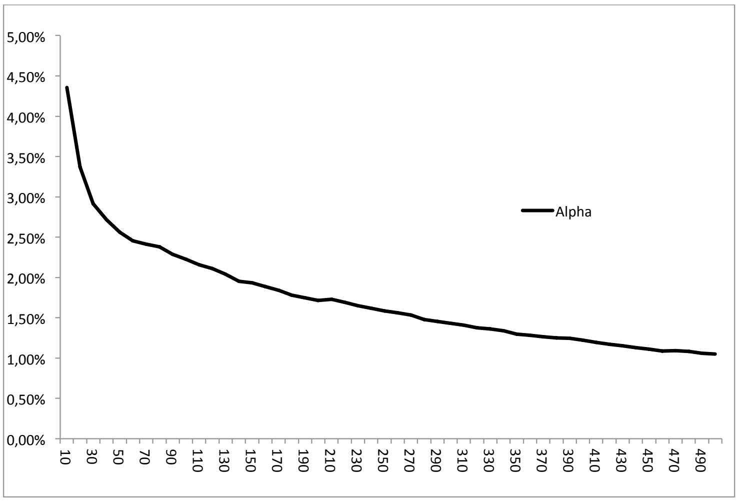


FIGURE 3.6: **Scalability in Risk Arbitrage**

This graph shows annual four factor alphas in the period from January 1995 to December 2012 for different levels of initial capital (in USD millions). All the optimized portfolios are estimated out-of-sample using all eight deal characteristics shown in Table 11 and the used transaction cost functions are displayed in table 9 column 3.



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