# Essays in Empirical Finance

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This thesis consists of three stand-alone essays in the funds management literature. The first essay examines the rationales for investing in closed-end funds (CEFs). Recent theory argues CEF serves as an ideal investment vehicle for investors who seek to gain exposure to illiquid securities and yet wish to avoid the high cost of transactions attached to such securities. Consistent with the predictions, this study finds CEF investors tend to avoid costly securities that the CEFs have already invested into. Further tests show that investors with short-term investment horizon and investors with preferences towards small-cap value securities are driving the results. More importantly, these results can be generalizable to the U.K., suggesting that they are applicable to other markets with significant CEF industries.

The second essay looks at the performance of hedge fund option strategies. This study utilizes a large sample of hedge fund managers' option holdings directly from their Form 13F filings for the period between 1999 and 2012. A direct construction of a hypothetical tracking portfolio that mimics these hedge fund option strategies yields significant negative monthly returns. These results survive a series of robustness tests such as alternative performance evaluation methodologies, different assumptions on option characteristics, and subsample analyses. Furthermore, there is no performance differential between option strategies implemented by hedge funds and by other institutional managers, who are often deemed to be less sophisticated. Taken together, this study does not support the view that hedge fund managers are skillful in executing informed trades in the options market.

The third essay investigates the value of institutional brokerage relationship in the mutual fund industry. Specifically, this study exploits the recent collapse of Lehman Brothers on September 15, 2008 as a natural experimental setting to examine the performance of Lehman mutual fund clients subsequent to the collapse. This study finds Lehman clients with concentrated brokerage networks and those with specialization in small-cap securities are adversely affected. Using a difference-in-difference (DiD) approach, these client funds experience significant drop in risk-adjusted returns. Collectively, the study confirms the view that mutual funds leverage significantly on their relationship capital with the brokers.

# Essays in Empirical Finance

Kok Keng Siaw

A thesis in fulfillment of the requirements for the degree of

Doctor of Philosophy

School of Banking and Finance

UNSW Business School

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# Abstract

This thesis consists of three stand-alone essays in the funds management literature. The first essay examines the rationales for investing in closed-end funds (CEFs). Recent theory argues CEF serves as an ideal investment vehicle for investors who seek to gain exposure to illiquid securities and yet wish to avoid the high cost of transactions attached to such securities. Consistent with the predictions, this study finds CEF investors tend to avoid costly securities that the CEFs have already invested into. Further tests show that investors with short-term investment horizon and investors with preferences towards small-cap value securities are driving the results. More importantly, these results can be generalizable to the U.K., suggesting that they are applicable to other markets with significant CEF industries.

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*"Empty your mind.. be formless, shapeless, like water. If you put water into a cup, it becomes the cup. You put water into a bottle, it becomes the bottle. You put it in a teapot it becomes the teapot. Water can flow, or it can crash. Be water my friend."*

Bruce Lee (Nov 27, 1940 - July 20, 1973)

# Contents

# List of Figures

# List of Tables

# List of Abbreviations

APE: average partial effect

ATM: at-the-money

CEF: closed-end fund

CRSP: Centre for Research in Security Prices

CSS: Cherkes, Sagi, and Stanton (2009)

DGTW: Daniel, Grinblatt, Titman, and Wermers (1997)

DiD: difference-in-differences

DITM: deep-in-the-money

DOTM: deep-out-of-the-money

EDGAR: Electronic Data Gathering, Analysis, and Retrieval

IPO: initial public offering

ITM: in-the-money

OTM: out-of-the-money

MFDB: Mutual Fund Database

MNL: multinomial logit

NAV: net asset value

REIT: real estate investment trust

SEC: Securities and Exchange Commission

TNA: total net asset

# Chapter 1

# Introduction

## 1.1 Background and Objectives

While direct accessibility to financial markets has improved significantly over time, the investment management industry continues to serve as an important intermediary for investors. It allows investors to delegate their excess capitals to professional money managers, who then provide a wide range of investment services in return for management fees. These services often include access to managerial investment expertise, increased portfolio diversification, and reduced transactions costs.

Perhaps the sheer size of the investment management industry underscores the critical role it plays in the financial market. According to the Investment Company Institute, U.S. registered investment companies have the largest assets under management in the world, estimated at \$18.2 trillion as of June 2014. Table 1.1 shows total net assets (TNAs) under management for different categories of funds from 1997 to 2014.[1] Collectively, these traditional registered investment companies serve nearly half (43.4%) of all U.S. households.

Table 1.1: Investment company assets in 2014.

This table reports the U.S. investment company TNAs by type (`http://www.icifactbook.org/fb_ch1.html`). TNAs are expressed in billions of dollars.

| Year | Mutual funds | Closed-end funds | Exchange-traded funds | Unit investment trusts | Total |
|---|---|---|---|---|---|
| 1997 | 4,468 | 152 | 7 | 85 | 4,711 |
| 1998 | 5,525 | 156 | 16 | 94 | 5,790 |
| 1999 | 6,846 | 147 | 34 | 92 | 7,119 |
| 2000 | 6,965 | 143 | 66 | 74 | 7,247 |
| 2001 | 6,975 | 141 | 83 | 49 | 7,248 |
| 2002 | 6,383 | 159 | 102 | 36 | 6,680 |
| 2003 | 7,402 | 214 | 151 | 36 | 7,803 |
| 2004 | 8,096 | 253 | 228 | 37 | 8,614 |
| 2005 | 8,891 | 276 | 301 | 41 | 9,509 |
| 2006 | 10,398 | 297 | 423 | 50 | 11,168 |
| 2007 | 12,000 | 312 | 608 | 53 | 12,974 |
| 2008 | 9,603 | 184 | 531 | 29 | 10,347 |
| 2009 | 11,113 | 223 | 777 | 38 | 12,151 |
| 2010 | 11,833 | 238 | 992 | 51 | 13,113 |
| 2011 | 11,632 | 242 | 1,048 | 60 | 12,982 |
| 2012 | 13,052 | 264 | 1,337 | 72 | 14,725 |
| 2013 | 15,035 | 279 | 1,675 | 87 | 17,075 |
| 2014 | 15,852 | 289 | 1,974 | 101 | 18,217 |

[1] Available at `http://www.icifactbook.org/`.

Moreover, the most recent decade has witnessed the growth of alternative investment vehicles, notably in the hedge funds industry.[2] Unlike traditional registered investment companies, the hedge fund industry is not subject to heavy regulation. It has several distinctive features, such as flexible investment strategies (e.g., short-selling, lock-up periods, derivative investments), opaque information environments (e.g., confidential filings), and asymmetric managerial compensations structure (e.g., high watermarks and bonus incentives). Therefore, hedge funds tend to display very different return characteristics from traditional investment schemes, making them an attractive investment option for investors who wish to further improve their portfolio risk–return characteristics.

As the financial market grows increasingly complex, it is more important than ever for investors, academic researchers, and practitioners to develop a deeper understanding on these investment vehicles. This dissertation contributes to the literature by providing three independent essays, each with a distinct research question written on the following areas: 1) CEFs, 2) hedge funds, and 3) mutual funds.

## 1.2 Essay on CEFs

Chapter 2 of the thesis concerns the rationale for investing in CEFs. While the industry itself represents a small segment of the world of registered investment companies (see Table 1.1), an abundance of academic papers have been written on it, with a

[2]Unfortunately, there is no universally accepted definition on what constitutes a hedge fund. Thus, it is not easy to put a definite number on the industry size. For instance, Preqin, a leading source of data and intelligence for the alternative assets industry, puts the U.S. based hedge fund industry size at \$1.74 trillion as of September 2013 (`https://www.preqin.com/docs/reports/Preqin_Special_Report_US_Hedge_Fund_Industry_Sep_13.pdf`). Alternatively, CNBC reports the hedge fund industry size is approaching \$2.6 trillion managed by $11,000$ funds (`http://www.cnbc.com/2014/08/29/industry-snapshot-26-trillion-in-11000-funds.html`).

significant emphasis on CEF discount/premia behavior.[3] Arguably, one of the most influential academic papers written on the CEF discount is by Lee et al. (1991), who propose the well-known investor sentiment theory: Following this premise, a stream of papers was spawned, extending the study of CEF discounts in various directions.[4]

Despite extensive coverage of the CEF discount/premia behavior, there is little documentation on the unique role CEFs play in the market. Earlier studies by Fama and Jensen (1983a,b), Chordia (1996), Nanda et al. (2000), Deli and Varma (2002) have hinted CEFs tend to hold more illiquid securities than most open-end funds. Building on these insights, Cherkes et al. (2009) propose a liquidity-based theory that argues CEFs "*offer a means for investors to buy illiquid securities, without facing the potential costs associated with direct trading*" (p. 257). Thus, the first contribution of this thesis to the literature is to apply the above rationale to the data by directly testing whether investors perceive CEFs as ideal investment vehicles to gain illiquidity exposure.

Our empirical innovation lies in observing holdings of CEFs by a significant group of investors while simultaneously tracking the portfolios of assets held by the CEFs. This allows us to infer whether investors choose to invest in illiquid securities directly or to gain indirect exposure to these illiquid securities via investment in CEFs. We find strong evidence in support of the theory's predictions: Investors are more likely to invest in CEFs to gain exposure to the underlying securities if these securities are very illiquid. Economically, we find a change of two standard deviations change

[3]The CEF discount/premia is defined as the difference between the share price traded in the exchange and the fund's underlying net asset value (NAV). If the share price is below the NAV then the fund is said to be traded at a discount. Similarly, if the share price is above the NAV, the fund is said to be traded at a premium.

[4]Examples include portfolio illiquidity (Deli and Varma (2002), Cherkes et al. (2009)), managerial performance (Chay and Trzcinka (1999)), agency costs (Barclay et al. (1993)), and distribution policies (Johnson et al. (2006), Jay Wang and Nanda (2011), Cherkes et al. (2014)). For excellent reviews on earlier research, see Dimson and Minio-Kozerski (1999) and Cherkes (2012).

in the underlying securities' illiquidity level raises the likelihood of observing an indirect investment by 6.3%, up from 28.1%.

Furthermore, we show that transient investors, who have a high demand for liquidity and shorter investment horizons, and small-cap value-oriented investors, who face high transaction costs, are particularly attracted to CEF liquidity attributes. Extending our analysis to the U.K. CEF industry yields similar insights, suggesting that the theory's prediction is generalizable outside of the U.S. market. Importantly, this essay demonstrates the benefits of the closed-end structure observed in real estate investment trusts (REITs), listed private equities, and secondary market traded hedge funds, which also specialize in similarly illiquid assets.

## 1.3 Essay on Hedge Funds

Chapter 3 of the thesis devotes itself to the hedge fund industry. Hedge funds, by their nature, are secretive and opaque. The literature has failed to come up with an unambiguous answer on whether hedge funds can earn abnormal returns, due partly to the difficulty in obtaining bias-free databases.[5] For instance, earlier studies by Ackermann et al. (1999) and Brown et al. (1999) indicate hedge funds can deliver positive alphas for investors. However, subsequent studies by Asness et al. (2001), Amin and Kat (2003), Kat and Palaro (2006), and Griffin and Xu (2009) overturn the statements, concluding hedge funds do not deliver alphas.

Other hedge fund studies also attempt to relate hedge fund performance to fund characteristics. For instance, Aragon (2007) reveals hedge funds with lockup restrictions yield, on average, higher excess returns than those of non-lockup funds,

[5] Hedge funds database are extremely difficult to work with. For example, both Aiken et al. (2012) and Agarwal et al. (2013a) show hedge fund commercial database can be subject to self-reporting bias.

suggesting that share restrictions are an effective tool for funds with significant exposure to illiquid assets. Agarwal et al. (2009) also document that hedge funds with greater managerial incentives and discretion tend to deliver superior performance. Further, Agarwal et al. (2013b) and Aragon et al. (2013) suggest hedge funds that possess private information are more likely to seek confidential treatments for their trading strategies.

On the other hand, the topic of the hedge fund use of derivative securities is under-researched. There are two views on how hedge funds use derivative securities: hedging and speculation. On the one hand, Chen (2011) finds hedge funds that use derivative securities have lower fund risks, engage in less risk-shifting, and are less likely to be liquidated but show no significant enhancement in return performance. These results can be interpreted as a hedging story in which fund managers employ derivative contracts to manage/reduce their portfolio risks. Aragon and Martin (2012), on the other hand, argue hedge fund managers are skilled in executing informed trades in the options market. The authors examine 250 randomly selected hedge fund managers' option positions and show these positions reflect significant timing and selectivity skills, indicating a speculation story.

Motivated by the above findings, we re-examine the results on hedge fund options trading strategy performance. Our paper differs from that of Aragon and Martin (2012) in two ways. First, our sample is much larger, consisting of 932 unique hedge fund managers whose option holdings are sourced directly from 13F filings from 1999 to 2012. Second, we improve on the authors' empirical methodologies in detecting hedge fund option investment skills. To our surprise, there is no material evidence showing these hedge fund option strategies can earn significant positive returns, as documented in Aragon and Martin (2012). Instead, a quarterly tracking portfolio of options constructed to mimic hedge funds option strategies yields significant negative monthly returns ranging from $-1.59\%$ to $-0.89\%$. These results are not driven by a performance evaluation approach or subsample analyses. Further tests also reveal it is not possible to discern between the performance of options trading strategies implemented by hedge fund managers and of those implemented by other, less sophisticated institutional managers.

Taken together, the results are interpreted as rejecting the null hypothesis that states hedge fund managers are skilled in using options to speculate in the market. However, one limitation associated with our study is our inability to distinguish between the following alternative hypotheses: whether hedge fund managers fail to execute informed trades in the options market or merely engage the options market for hedging purposes. Nonetheless, evidence from the literature seems to favor the hedging story as documented in Chen (2011).

## 1.4 Essay on Mutual Funds

Chapter 4 of the thesis focuses on the mutual fund industry, the dominant segment within registered investment companies (see Table 1.1). it is no surprise, given the industry's massive size, that numerous research papers have investigated the relation between mutual fund performances, return persistency, and fund flows.[6] Recent literature also establishes important determinants of mutual fund performance. These include, for instance, managers' portfolio concentration levels (Kacperczyk et al. (2005), Sapp and Yan (2008)), the degree of managerial reliance on public infor-

[6]Two common techniques are used to evaluate mutual fund performance: the factor-model based regression approach (Jensen (1968), Carhart (1997)) and a characteristic-based benchmark approach (Daniel et al. (1997), (DGTW)). To date, the evidence on whether mutual fund managers outperform the stock market and whether such performance can persist remains mixed (Chen et al. (2000), Berk and Green (2004), Berk and van Binsbergen (2015)). As for the mutual fund flow literature, most papers concur that flows are highly dependent on past performance. In particular, these studies show there is a convex flow-performance relation; that is, U.S. investors chase winners more intensively than they sell poorly performing funds (Ippolito (1992), Sirri and Tufano (1998)

mation (Kacpercyzk and Seru (2007), managers' unobserved actions (Kacperczyk et al. (2008)), and the degree of deviation from the fund's designated benchmark (Cremers and Petajisto (2009), Amihud and Goyenko (2013)).

In comparison, fewer studies consider the role of the sell-side industry and mutual fund performance, notwithstanding the billions of brokerage commission dollars the mutual fund industry pays each year (Goldstein et al. (2009)). We identify two unresolved research issues in this line of literature. The first regards whether fund managers benefit from the additional premium brokerage services offered by the sell-side industry. On the one hand, some studies contend there is value added from utilizing sell-side industry services, which can lower managers' execution costs (Anand et al. (2011)), improve manager's ability to select securities (Xie (2014)), receive favorable initial public offering (IPO) allocations (Reuter (2006)), gain access to management conferences (Green et al. (2014)) and liquidity support (Aitken et al. (1995)). On the other hand, studies also point out problems associated with these institutional brokerage relationships, such as the detrimental effects of excessive churning by fund managers on their performance (Edelen et al. (2012), Edelen et al. (2013))). The second issue is that these studies often do not provide clear answers as to what portion of the observed fund's performance can be attributed to the relationship capital managers have with their brokers.

We contribute to the literature by addressing these two interrelated problems. We obtain information on mutual fund brokerage networks directly from their N-SAR filings, which allows us to identify and track the relationship these funds have with their brokers. To enable a causal interpretation on the results, our empirical design exploits the recent collapse of Lehman Brothers on September 15, 2008 as an exogenous shock to the brokerage relationships mutual funds had with Lehman. Intuitively, we hypothesize the demise of Lehman constituted an unexpected interruption on its relationships with fellow mutual fund clients. Consequently, if there were value for fund managers maintaining a stable relationship with their brokers, we would expect these Lehman mutual fund clients to suffer a drop in their fund alphas because of the damaged brokerage relationship.

Using a DiD approach, we show Lehman mutual fund clients with concentrated brokerage networks and that specialize in small, hard-to-value securities experienced significant return deteriorations in the aftermath. Specifically, we estimate such perturbations in institutional brokerage ties translate to a drop in risk-adjusted returns averaging between 20.3 and 53.5 basis points per month. Collectively, our results support the view that information and research services from the sell-side industry are indispensable inputs in enhancing mutual fund performance.

## 1.5 Thesis-related Presentations

The research in this dissertation has been presented at both domestic and international conferences as specified below.

- Chapter 2:
  - 2014 Conference on Professional Asset Management (Rotterdam, Netherlands)
  - 2014 Northern Finance Association (Ottawa, Canada)
  - 2014 Financial Integrity Research Network Conference (Sydney, Australia)
  - 2014 Conference on Asia-Pacific Financial Markets (Seoul, Korea)
  - 2014 Financial Management Association Asian Conference (Tokyo, Japan)
  - 2014 Financial Management Association Annual Conference (Nashville, U.S.)
  - 2014 Midwest Finance Association Conference (Orlando, U.S.)
  - 2014 Southwestern Finance Association Conference (Dallas, U.S.)
  - 2014 Asian Finance Association Conference (Bali, Indonesia)
  - 2014 Financial Markets and Corporate Governance Conference (Brisbane, Australia)
  - 3rd SIRCA Young Researcher Workshop (Sydney, Australia)
  - 4th Behavioral Finance and Capital Markets Conference (Adelaide, Australia)
  - 2013 Australasian Finance and Banking Conference (Sydney, Australia)

- Chapter 3:
  - 2015 Auckland Finance Meeting (Auckland, New Zealand)
  - 2015 Financial Markets and Corporate Governance Conference (Perth, Australia)
  - 2015 SIRCA Pitching Symposium (Sydney, Australia)
  - 2014 International Conference on Futures and Derivative Markets (Shanghai, China)
  - The Reserve Bank of Australia
- Chapter 4:
  - Monash University (Kuala Lumpur, Malaysia)

# Chapter 2

# An Empirical Analysis of The Liquidity Motive for CEFs

## 2.1 Abstract

The liquidity-based theory of CEFs argues that investors are attracted to the vehicles to gain indirect exposure to illiquid assets, thus avoiding high trading costs. We provide support for this rationale. Directly comparing CEF holdings with those of CEF investors, we find that the latter are less likely to invest stocks already in CEFs' portfolios, preferring to gain exposure to such illiquid stocks via the CEFs. We corroborate U.S. with U.K. CEF industry evidence. The results may be informative for understanding closed-end structures observed in REITs, listed private equities, and secondary market traded hedge funds.

## 2.2 Introduction

The existence of CEFs is one of the most intriguing and unresolved puzzles in finance research. For instance, an overwhelming literature shows that the share prices of these listed investment vehicles generally trade at a substantial and long-lasting discount to their NAV from inception, bringing into question the rationale for investing in CEFs and their very existence.[1] Cherkes et al. (2009) liquidity-based theory argues that CEFs "*offer a means for investors to buy illiquid securities, without facing the potential costs associated with direct trading*" (p. 257). This study is an empirical test of this rationale. We test the hypothesis that investors use CEFs to gain exposure to illiquid securities they would prefer not to invest indirectly. To the best of our knowledge, this is the first paper to directly investigate whether investors choose CEFs for liquidity purposes.

In modeling the dynamics of CEF premiums and discounts, Cherkes et al. (2009) (henceforth "CSS") argue that the ability of CEFs to package a portfolio of illiquid stocks into a more accessible and tradable security is their major selling point for investors. The CSS theory is premised on the observation that, unlike open-end funds, which allow investors to directly redeem their money, CEF investors can only do so by trading their shares in the secondary market. Without the pressure from unexpected cash flows into and out of their funds, CEF portfolio managers can devise long-term trading strategies to participate in illiquid segments of the market. Thus, a CEF effectively serves as an investment vehicle for investors who wish to diversify their portfolios into a less liquid market but at the same time do not want to pay the transaction costs associated with excessive trading. Based on this insight, CSS

[1] Lee et al. (1990) summarize the four anomalies related to CEFs as follows: (1) CEFs are often brought to market at a premium, (2) CEF share prices subsequently trade at a discount after an IPO (3) the CEF discount fluctuates widely across time, and (4) CEF share prices converge to their NAVs upon open-ending. See Cherkes (2012) for a review of the literature.

argue the CEF discounts/premiums arise as a trade-off between managerial expenses and the liquidity services. The theory gives us a liquidity lens with which to view the CEF industry: Do investors value CEFs as ideal investment vehicles to gain illiquidity exposures? How does the availability of CEFs affect investors' portfolio delegation decisions?

Further motivation for our pursuit of these questions comes from pronouncements of how regulators and industry practitioners view the role of CEFs. According to the U.S. Securities and Exchange Commission (SEC):[2] "*CEFs are permitted to invest in a greater amount of "illiquid securities than are mutual funds. (An 'illiquid' security generally is considered to be a security that cannot be sold within seven days at the approximate price used by the fund in determining NAV.) Because of this feature, funds that seek to invest in markets where the securities tend to be more illiquid are typically organized as CEFs.*" This view is shared by the Closed-End Fund Association, which states "*the CEF structure [is] advantageous for investing in specialized areas such as less liquid securities or markets, venture capital opportunities, real estate, and private placements.*"[3] Blackrock, one of the largest professional money management firms, also regards liquidity provision as a unique advantage of CEFs over the open-end funds.[4] In this paper we provide systematic evidence in support of these views.

The innovation of our empirical design lies in observing holdings of CEFs by a significant group of investors while simultaneously tracking the portfolios of assets held by the CEFs. To find out whether liquidity considerations attract investors to CEFs we compare CEF investors' portfolio holdings to the holdings of the CEFs in which they invest.[5] We test the CSS theory by investigating the role CEFs play

[2] Available at `http://www.sec.gov/answers/mfclose.htm`.

[3] Available at `http://www.cefa.com/Learn/Content/CEFBasics/advantages.fs`.

[4] See "A Guide to Investing in Closed-End Funds", available at `http://www.blackrock.com/investing/literature/investor-education/guide-to-investing-cefs.pdf`.

[5] As registered investment companies, CEFs are required to periodically file their holdings with

in investors' portfolio delegation decisions. CEFs are structured to pursue specific investment objectives and securities as stated in their prospectuses. Based on the liquidity rationale for CEFs, we hypothesize that CEF investors being aware of CEF holdings, are less likely to invest in securities that are held by the CEFs. Moreover, the premise of the theory is that this likelihood is an increasing function of the stock's illiquidity. In other words, investors outsource the investment and management of illiquid securities to CEFs. We illustrate this logic with an example. Consider an investor in the process of formulating an investment strategy between two equally illiquid segments in the market, A and B. Suppose that in this hypothetical market there is only one CEF and it invests solely in Segment A. Under this setup, it is straightforward to see that the investor's only option to gain exposure to Segment B is to invest in it directly, should she choose to invest. On the other hand, the investor has three choices regarding investment strategies in Segment A: (1) a direct investment, (2) an indirect investment via the CEF, or (3) both direct and indirect investments. CSS argue that the second option is perceived to be more attractive, since the liquidity level of the CEF is deemed to be higher than its underlying assets, allowing the investor to liquidate holdings in the CEF quickly should an unexpected liquidity shock occur.[6]

Our analysis is based on the population of U.S. institutional investors whose ownership of all CEFs ranges from 6% to 13% over the period 2003-2010. By comparison, in the U.K., institutional investors account for over 60% of CEF ownership (see, for example, J.P. Morgan (2011)). Motivated by the distinct institutional settings between the two markets, we also offer insights on the generalizability of CSS theory

the U.S. SEC. Such information is publicly available, enabling CEF investors to investigate the underlying securities as part of their due diligence processes.

[6] In reality CEFs invest in many more securities, including those that investors may not wish to gain exposure to. We assume that where the undesirability of such stocks dominates the liquidity-based investment motive for choosing CEFs, the disincentive it represents has the effect of reducing the likelihood of finding results in support of our hypotheses.

by replicating our results in the U.K. CEF industry.[7]

We find direct evidence of the attractiveness of CEFs in support of the liquidity-based theory: The likelihood of observing a manager's indirect investment via a CEF increases as the level of illiquidity in securities held by the CEF goes up. Economically, a two standard deviation change in the stock's liquidity level raises the probability of an institution outsourcing the investment and management of illiquid securities to CEFs by 6.3%, up from 28.1%. These results show that liquidity-sensitive investors gain exposure to illiquid securities through CEFs, consistent with the liquidity-based explanation.

We conduct further analyses to stress test and bolster our headline findings. First, we are interested in whether the liquidity attributes of CEFs attract subsets of investors who can reasonably be expected to value this characteristic. To do this, we partition our sample of institutional investors based on their investment horizon and style dimensions. Interestingly, transient or short-term investors, characterized by having high portfolio turnover, are more likely to invest in CEFs compared to dedicated long-term investors. This distinct asymmetric investment behavior suggests transient investors, who have high demand for liquidity and shorter investment horizons, use CEFs to gain long-term exposure to illiquid securities. In contrast, CEFs do not play a vital role in the portfolio compositions of dedicated investors likely because they can opt for direct investment themselves due to the long-term nature of their investment strategies. In terms of investment style, small-cap value-oriented investors, who face high transaction costs, rely the most on outsourcing the management of illiquid securities to CEFs. The economic magnitude is significant: the probability of observing manager's indirect investment via CEFs goes up by 7.8%

[7] Apart from stress testing the generalizability of the CSS theory, an additional contribution of our paper is thus to offer parallel analyses based on both the U.S. and U.K. CEF industries. Despite the facts that the U.K. CEF industry has several notable distinct features from the U.S. market, most previous papers focus exclusively on the U.S. market.

for a two standard deviation change in the stock's illiquidity level. Such effects are weaker for large-cap-oriented or growth-oriented investors.

Second, we provide evidence that it is the closed-end (as compared to open-end) nature of CEFs that gives them the special liquidity provider status we document in this paper. Chen et al. (2004) show that mutual fund returns deteriorate with fund size especially in small-cap funds that are more sensitive to asset fire sales in the event of fund runs. Chen et al. (2010) also model the destabilizing fund flow implications of opened-end fund structures and conclude that this vulnerability is a consequence of the liquidity of open-end funds' underlying asset. While both CEFs and open-ended small-cap mutual funds invest in small-cap stocks, we show that open-end funds are attracted to more liquid small-cap stocks. In contrast, CEF stock investment is positively related to the level of small-cap stock illiquidity. This finding is robust to alternative econometric specifications and suggests that CEFs are indeed well-suited for illiquid investment purposes.

Finally, we extend our analyses to the U.K. investment trust or CEF industry, that, by being dominated by institutional instead of individual investors, provides a unique opportunity to test the generalizability of the CSS theory. We find that U.K. institutional managers are also more likely to outsource illiquid investments to CEFs. The estimated influence of stock illiquidity on the managerial outsourcing decision is positive and highly significant. A two standard deviation increase in stock illiquidity leads to an increase in the probability of observing managerial investment outsourcing by 8.9%, up from 27.1%. These results are comparable to our U.S. sample analysis, if not stronger.

Our paper contributes to the literature in two ways. First, based on comprehensive data on CEFs, including their holdings, we provide a structured analysis of liquidity provision as a CEF attribute that, besides the CSS theory paper, is only indirectly hinted at in the limited related empirical literature.[8] Deli and Varma (2002) find that investment funds that specialize in less liquid securities are more likely to be structured as closed- rather than open-ended, consistent with Fama and Jensen (1983a,b) predictions about organizational choice relative to the control value of redeemable shares.[9] Second, while our central theme is relevant to the CEF literature, the findings we document in this paper contribute to our understanding of other closed-end investment vehicles specializing in similarly illiquid assets. These include hedge funds that offer secondary market trading (Ramadorai (2012)), listed private equities (Cumming et al. (2011)), and REITs (Benveniste et al. (2001), Ciochetti et al. (2002)).

The remainder of this chapter is organized as follows. Section 2.3 discusses our data and variable construction process. Section 2.4 presents the empirical results. Section 2.5 concludes.

[8]We acknowledge there are other advantages of investing in CEFs, including the opportunity to buy at a discount (Malkiel and Firstenberg (1978)), the potential to leverage up the investments (Elton et al. (2013)), and lower expense ratios. As well, there are other well-established theories that explain the existence of CEFs in spite of the well-known NAV discount, notably Lee et al. (1991) investor sentiment theory in which operators of CEFs take advantage of individual investors who buy CEFs at times when they are overly optimistic about the market. This turns the observed discount into premium. As a consequence, the entrepreneurs respond to this excessive demand by offering individual investors an overprice CEFs that do not reflect the fundamentals of their underlying assets.

[9]Fama and Jensen (1983a,b) argue that the existence of open-end funds is explained by the threat of investors exiting the fund due to the redeemable nature of its shares. However, this control value may be outweighed by trading and agency costs related to the illiquidity of fund assets or the difficulty of observing asset prices, giving rise to the closed end form of investment funds.

## 2.3 Data

We obtain a survivorship bias-free sample of U.S. CEFs from the Morningstar Direct database covering the period January 2003 to June 2010.[10] Morningstar classifies the CEFs into the following categories: domestic equity funds, foreign equity funds, taxable bond funds, municipal bond funds, sector funds, and others (balanced funds, allocation funds, and convertible funds). Using a combination of fund names, tickers, and inception dates, we hand-match the Morningstar CEFs in our sample with those in the CRSP database. We collect CEF information such as the TNA, share price premium, gross expense ratio, turnover ratio, as well as their detailed portfolio holdings. The resulting sample comprises of 851 CEFs.

Table 2.1 Panel A reports the summary statistics of the CEFs in our study. The sample consists of over $250 billion in total assets by market capitalization in our CEF sample as of June 2010, which is almost 80% of the U.S. CEF market's total AUM, according to Investment Company Institute 2013 figures.[11] Municipal bond CEFs are the largest segment in the industry, with a total of 352 funds and an average fund size of $216.43 million. There are 66 domestic equity CEFs and 95 foreign equity funds, with average fund sizes of $380.13 million and $243.82 million, respectively.

[10] Our initial sample yields 1,015 CEFs. We crosscheck the data with the CRSP database (CEF share codes 14, 15, 24, 44, or 74). We find 1,117 CEFs in the CRSP databases, which closely correlates with the Morningstar data.

[11] Available at `https://www.ici.org/pdf/2013_factbook.pdf`.

Table 2.1: CEFs summary statistics.

Panel A presents summary statistics on U.S. CEFs. Our sample period spans from January 2003 to June 2010 with a total of 851 funds. Based on Morningstar classifications, there are six categories of CEFs: domestic equity funds, foreign equity funds, municipal bond funds, taxable bond funds, sector funds, and others (balanced funds, alternative funds, and convertible funds). *CEF TNA* is TNA value of the CEF, expressed in millions of dollars. *CEF Premium*, in percentage terms, is defined as the difference between the CEF share price and the NAV of the CEF divided by the CEF share price. *CEF GrossExp*, in percentage terms, represents total gross expenses (net expenses with waivers added back in) divided by the fund's average net assets. *CEF Turnover*, in percentage terms, measures the portfolio manager's trading activity by taking the lesser of purchases or sales and dividing by average monthly net assets. Panel B shows the CEF portfolio allocations in various asset classes such as US equity, non-US equity, bond, cash, and others, averaged across the whole sample period. Panel C and D present the U.K. CEFs summary statistics and portfolio allocations in various asset classes. Analogous to the U.S. sample, we classify funds into three categories: domestic equity funds, foreign equity funds, and others.

**Panel A: U.S. CEF information**

| Category | Number | *CEF TNA* | *CEF Premium (%)* | *CEF GrossExp (%)* | *CEF Turnover (%)* |
|---|---|---|---|---|---|
| Domestic equity | 66 | 380.13 | -6.28 | 1.31 | 59.61 |
| Foreign equity | 95 | 243.82 | -7.11 | 1.53 | 60.81 |
| Municipal bond | 352 | 216.43 | -3.14 | 1.32 | 25.97 |
| Taxable bond | 228 | 289.83 | -2.68 | 1.65 | 102.25 |
| Sector | 66 | 370.43 | -6.37 | 1.93 | 45.08 |
| Others | 44 | 283.71 | -4.65 | 1.62 | 80.20 |

**Panel B: U.S. CEF portfolio allocation**

| Category | US equity (%) | Non-US equity (%) | Bond (%) | Cash (%) | Other (%) |
|---|---|---|---|---|---|
| Domestic equity | 82.10 | 7.92 | 1.52 | 5.95 | 2.57 |
| Foreign equity | 11.53 | 66.37 | 6.35 | 2.33 | 2.84 |
| Municipal bond | 0.01 | 0.04 | 100.51 | -0.15 | -0.37 |
| Taxable bond | 0.56 | 0.27 | 88.23 | 3.45 | 7.34 |
| Sector | 61.79 | 14.89 | 5.68 | 4.04 | 13.31 |
| Others | 33.57 | 7.85 | 36.84 | 3.48 | 18.69 |

**Panel C: U.K. CEF information**

| Category | Number | *CEF TNA* | *CEF Premium (%)* | *CEF GrossExp (%)* | *CEF Turnover (%)* |
|---|---|---|---|---|---|
| Domestic equity | 105 | 137.63 | -8.27 | 1.21 | 43.54 |
| Foreign equity | 191 | 245.37 | -11.69 | 1.42 | 61.34 |
| Others | 486 | 102.30 | -13.53 | 2.41 | 40.31 |

**Panel D: U.K. CEF portfolio allocation**

| Category | US equity (%) | Non-US equity (%) | Bond (%) | Cash (%) | Other (%) |
|---|---|---|---|---|---|
| Domestic equity | 83.70 | 9.76 | 2.45 | 0.37 | 4.25 |
| Foreign equity | 14.02 | 74.60 | 4.01 | 2.93 | 6.08 |
| Others | 24.35 | 55.14 | 9.79 | 10.56 | 11.79 |

Consistent with documented empirical regularities, equity funds have deeper discounts than bond funds (e.g., Elton et al. (2013)). For example, the difference in discounts between typical foreign equity and taxable bond funds is 4.43%. Fund fees range from 1.31% to 1.93% and are higher for funds specializing in alternative investment and foreign securities, for example. Taxable bond funds appear to have the highest turnover ratio among all categories. In addition, bond funds generally have higher leverage ratios than equity funds. Panel B reports the CEF portfolio allocation across different asset classes. In general, CEFs adhere their investment mandates, with some exceptions. For instance, while foreign equity CEFs, on average, hold 66.37% of the assets in non-US equity, they also invest other asset classes such as US equity (11.53%) and US bonds (5.73%). Overall, the summary statistics of our CEF sample share similar characteristics with CEF samples used in recent studies (e.g., CSS, Elton et al. (2013), Wu et al. (2013)).

Our source of data for institutional holdings information is the Thomson Reuters S34 Master File, which originate from 13F filings. All institutional investment managers who exercise investment discretion over $100 million or more are required to report their portfolio holdings to the SEC under the Investment Securities Act of 1934. We define institutional ownership as the number of shares held by institutions over the total number of shares outstanding of the stock. We also classify institutions based on their investment horizon (transient, dedicated, or quasi-index) and investment style (large-cap growth, large-cap value, small-cap growth, or small-cap value) using Bushee (1998, 2001) classification schemes.[12] We obtain market and accounting information on equities from the CRSP and Compustat databases, respectively, including firm size, firm age, dividend yield, book-to-market ratio, month-end share

[12]The database does not have a unique identifier for each institution and, it provides inconsistent classifications from 1998 onward due to a known internal mapping error. We thank Brian Bushee for making the corrected identifier and institutional classification scheme available at `http://acct3.wharton.upenn.edu/faculty/bushee/IIclass.html`. See Bushee (1998), Bushee and Noe (2000), Bushee (2001), and Abarbanell et al. (2003) for further details.

price, stock volatility, cumulative returns, S&P 500 membership, and leverage ratio. These variables are used in the literature to explain the variation in institutional investment preferences (Gompers and Metrick (2001), Bennett et al. (2003)). To estimate security illiquidity, we obtain intraday equity trading data from the Trade and Quote database and compute the daily size-weighted relative effective spread as follows:

$$EffectiveSpread_{i,t} = \frac{1}{D}\sum_{d=1}^{D}\left(\frac{1}{N_d}\sum_{n=1}^{N_d} 2|P_{d,n} - M_{d,n}|\right),$$

where $N_d$ is the number of trades at day $d$, $A_{d,n}$ is the ask-price, $B_{d,n}$ is the bid-price, and $M_{d,n} = \frac{(A_{d,n}+B_{d,n})}{2}$. Then, we take their 90-trading day average; i.e. $D = 90$. The appendix in Section 2.6 provides detailed descriptions of the computational procedures and sources of information for all the variables defined in the paper.

Due to regulatory disclosure practices, our 13F institutional ownership data covers managers' holdings in U.S. domestic equity stocks only. For this reason, our subsequent analyses utilizing portfolio holdings concentrate solely on a subset of managers who invest in 65 domestic equity CEFs. In total, there are 650 institutional managers that invest in domestic equity CEFs over the sample period. While these disclosure imposed restrictions exclude foreign equity and bond CEFs from our main analyses, a positive outcome for our study is that equity CEFs are a homogenous asset class (see Panel B of Table 2.1) for which data to compute liquidity measures are readily available and well established in the literature.

In robustness tests (see Section 2.4.6), we repeat our main empirical analyses using the U.K. CEF industry, where CEFs are known as "investment trusts". Analogous to our U.S. sample, we first source a survivorship bias-free list of U.K. CEFs from the Morningstar Direct database. We classify our U.K. CEFs into three broad categories: domestic equity funds, foreign equity funds, and others.[13] We obtain portfolio hold-

[13]Using the Association of Investment Companies (AIC) classification scheme, a domestic equity

ings for both the U.K. CEFs and institutional investors from the Factset database. We collect market and accounting variables for U.K. stocks from the Compustat Global. Panel C presents our U.K. CEF sample statistics, consisting of 782 funds. There are 105 domestic equity CEFs and 191 foreign equity CEFs. Individual fund size is generally smaller than the U.S. counterpart, with average domestic equity CEFs' TNA being \$137.63 million. On average, the U.K. CEF industry is trading at discounts ranging between $-13.53\%$ and $-8.27\%$. Gross expenses and turnover ratios are generally comparable to the U.S. industry. A typical domestic equity CEF has an expense ratio of 1.21% and a turnover ratio of 43.54%. Similarly, as shown in Panel D of Table 2.1, the U.K. CEFs generally follow their investment mandates; with domestic equity CEFs investing 83.7% of their money in the U.K. market. Importantly, the overall exposure of the industry to the bond market is significantly lower than the case for U.S. As with the case of the U.S., to ensure sample homogeneity, we focus on the 105 U.K. domestic equity CEFs and the 376 institutional managers that invest in them.

CEF is one for which AIC classifies as "UK All Companies", "UK Equity & Bond Income", "UK Equity Income", "UK Growth & Income", and "UK Smaller Companies". A foreign equity CEF is one that is either specializing in a particular country (e.g., Latin America, North America), region (e.g., Europe, Asia Pacific), or globally. The remaining categories are classified as others, which typically include sector specialists and venture capital trusts.

## 2.4 Empirical Tests of the Liquidity-Based Theory of CEFs

### 2.4.1 Overview of Institutional Ownership of CEFs

To give a context to our empirical analysis, we first present trends in institutional ownership of U.S. CEFs. Figure 2.1(a) shows the average institutional ownership of CEFs in December of each year from 2003 to 2010. Institutional ownership of CEFs is around 5% in the early years (consistent with Weiss (1989)) but increases steadily over time to 13% in 2008. Figure 2.1(b) breaks down the CEF sample by investment category. Among the four categories, foreign equity CEFs have the highest institutional presence, with ownership ranges between 20% and 25% in the latter years. While the institutional ownership of domestic equity CEFs is higher than that of taxable bond CEFs, this trend has reversed since 2004 when institutional ownership for these two categories of CEFs is between 15% and 20%. Finally municipal bond CEFs attract the least institutional investor ownership, despite being the dominant sector in the industry.

Figure 2.1: Institutional ownership of U.S. CEFs.

Figure 2.1(a)

This figure presents the average institutional ownership of all categories of CEFs used in the sample in December of each calendar year. The sample period spans from 2003 to 2010.

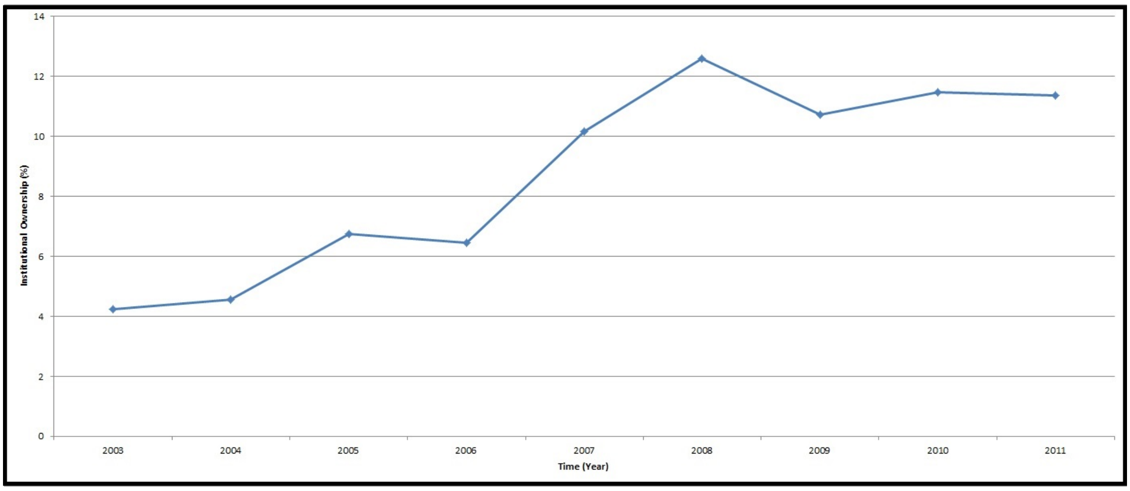
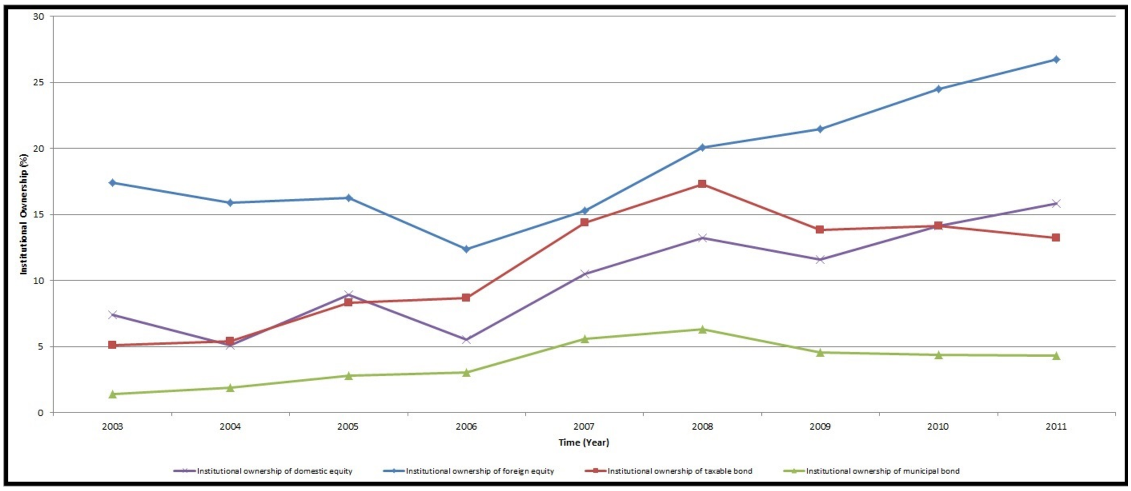



Figure 2.1(b)

This figure presents the average institutional ownership of different categories of CEFs in December of each calendar year. The sample period spans from 1990 to 2010. We categorize CEFs into domestic equity CEFs, foreign equity CEFs, taxable bond CEFs, and municipal bond CEFs.



### 2.4.2 The Role of CEFs In Portfolio Delegation Decisions

In this section, we test our hypothesis that, in line with the liquidity rationale for investing in CEFs, the likelihood of an institutional investors to hold a stock is decreasing with the investor's holding of a CEF that already owns the stock. Since the manager's investment decision (the dependent variable) is categorical in nature, we use the multinomial logit (MNL) model. Formally, we assume the manager is the main decision maker and needs to choose an appropriate investment choice for $i = 1, ..., N$ stocks. In particular, there are $J = 3$ investment choices associated with each stock $i$: (1) invest directly in stock $i$ as well as indirectly via CEFs, denoted $j = 0$; (2) invest directly in stock $i$ only, denoted $j = 1$; or (3) invest indirectly in stock $i$ via CEFs, denoted $j = 2$. Let $P_{i,j,k}$ be the probability that decision $j$ is made for stock $i$ by institution $k$. Then, under the MNL model, we obtain:

$$\begin{aligned}\ln\left(\frac{P_{i,j,k}}{P_{i,0,k}}\right) \quad = \quad & \beta_{0,j} + \beta_{1,j}\mathit{EffectiveSpread}_{i,k} + \beta_{2,j}\mathit{MarketCap}_{i,k} + \beta_{3,j}\mathit{Age}_{i,k} \\ & + \beta_{4,j}\mathit{Dividend}_{i,k} + \beta_{5,j}B/M_{i,k} + \beta_{6,j}\mathit{Price}_{i,k} + \beta_{7,j}\mathit{Volatility}_{i,k} \\ & + \beta_{8,j}\mathit{S\&P\ 500}_{i,k} + \beta_{9,j}\mathit{Return(t\text{-}3,t)}_{i,k} + \beta_{10,j}\mathit{Return(t\text{-}12,t\text{-}3)}_{i,k} \\ & + \beta_{11,j}\mathit{Leverage}_{i,k}, \qquad (2.1)\end{aligned}$$

where $i = 1, 2, ..., I_k$ are the $i^{th}$ holding of institutional managers of $k = 1, 2, ...K$ and $j = 1, 2$ are the investment choices. We use $j = 0$ as the base category. It is important to point out that our data are hierarchically structured since we are examining the security investment decisions for each individual institutional investor in our sample. For this reason, we cluster the standard errors at the investor level because investment decisions are more likely to be correlated within each institution. We also control for time fixed effects in our analysis by including a series of year dummies in our model. There are 650 unique managers who invest in at least one domestic equity CEF. The unconditional probabilities of observing co-investment, direct investment, and indirect investment are 26.38%, 44.20%, and 29.42%, respectively.

Table 2.2 presents the estimation results for Equation (2.1). In addition to reporting the estimated coefficients of the models and clustered-robust standard errors, we report the average partial effects (APEs) for the variables.[14] Consistent with the liquidity-based theory of CEFs, we see that investors are generally more willing to invest directly in liquid securities and less so for illiquid securities. This relation remains strong even after controlling for stock characteristics known to influence investor preferences. The APEs of *EffectiveSpread* is -0.028 and 0.023 for direct investment and indirect investment, respectively. To illustrate the economic magnitude of our finding, a change of one standard deviation below to one standard deviation above the mean of *EffectiveSpread* while holding all other variables at their means translates into a 6.3% increase in the probability that the investor will invest in the securities indirectly via a CEF. The probability of direct investment decreases by a similar magnitude, showing a distinct substitution effect. On one hand, small-cap securities also tend to increase the probability of investors choosing an indirect investment strategy (APEs $= -0.064$). On the other, institutional managers are more likely to invest into stocks that are part of the S&P 500 constituents. The estimated APE for $S\&P500$ stands at 0.064 and is highly significant. Other variables are also shown to be important determinants of manager's investment decisions. For instance, stocks that have lower dividend yield, less volatility, and less leverage are more likely to be outsourced to the underlying CEFs.

[14] Our choice of reporting is primarily motivated by Greene (2008), who states that current practice favors averaging the individual marginal effects when it is possible to do so instead of computing the marginal effects, which evaluates the expressions for the sample means of the data. Nevertheless, the difference between the two is usually marginal if the sample size is large enough.

Table 2.2: Institutional investment choices.

This table presents the estimation results of Equation (2.1). The MNL model takes the following form:

$$\begin{aligned}\ln\left(\frac{P_{i,j,k}}{P_{i,0,k}}\right) &= \beta_{0,j} + \beta_{1,j}\,\textit{EffectiveSpread}_{i,k} + \beta_{2,j}\,\textit{MarketCap}_{i,k} + \beta_{3,j}\,\textit{Age}_{i,k} + \beta_{4,j}\,\textit{Dividend}_{i,k} + \beta_{5,j}\,B/M_{i,k}\\ &\quad +\beta_{6,j}\,\textit{Price}_{i,k} + \beta_{7,j}\,\textit{Volatility}_{i,k} + \beta_{8,j}\,\textit{S\&P 500}_{i,k} + \beta_{9,j}\,\textit{Return(t-3,t)}_{i,k}\\ &\quad +\beta_{10,j}\,\textit{Return(t-12,t-3)}_{i,k} + \beta_{11,j}\,\textit{Leverage}_{i,k},\end{aligned}$$

where $i = 1, 2, ..., I_k$ are the $i^{th}$ holding of institutional managers of $k = 1, 2, ...K$ and $j = 1, 2$ are the investment choices. We use $j = 0$ as the base category. In particular, we denote $j = 0$ as representing the outcome when stock $i$ is concurrently held by both CEF investors and CEFs, $j = 1$ when it is held only by CEF investors, and $j = 2$ when it is held only by CEFs. *EffectiveSpread* is the size-weighted relative effective spread, averaged over the past 90 trading days. *MarketCap*, expressed in millions of dollars, is the firm's equity value, calculated as the number of shares outstanding multiplied by the month-end closing stock price. *Age* is the number of months the firm first appeared in the CRSP. *Dividend*, *B/M*, and *Price* are the dividend yield, book-to-market ratio, and quarter-end price of the stock. *Volatility* is the standard deviation of daily stock returns measured over the past 24 months, expressed in percentage terms. $S\&P500$ is a binary variable that takes the value of one if the security is included in the S&P 500 membership and zero , otherwise. *Return(t-3,t)* and *Return(t-12,t-3)*, expressed in percentage terms, are the cumulative returns of the stock over the past three months and over the nine months preceding the beginning of filing quarter, respectively. *Leverage*, expressed in percentage terms, is total debt over total assets. We use the logarithmic of *EffectiveSpread*, *MarketCap*, and *Age*. Year dummies are included in the models. All standard errors are clustered at the manager level and are shown in parentheses. The APEs are presented in square brackets. Number of institutional managers, number of unique stocks, and McFadden's $R$-squared are presented. For the MNL model, we also present the economic effects of *EffectiveSpread* on each of the predicted outcome. For example, to compute the economic effect of *EffectiveSpread* on direct investment, we add one standard deviation of *EffectiveSpread* to its mean and compute the predicted likelihood of observing direct investment using the estimated coefficients, holding all other control variables at their means. We also subtract the mean of *EffectiveSpread* by one standard deviation and compute the predicted likelihood of observing direct investment. We then compute the change in the predicted likelihood as the economic effect of *EffectiveSpread* on direct investment. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

- Continued on next page -

| Variables | Direct investment vs. co-investment | Indirect investment vs. co-investment |
|---|---|---|
| *Constant* | 2.277*** | 4.562*** |
| | (0.386) | (0.378) |
| *EffectiveSpread* | -0.079*** | 0.075*** |
| | (0.014) | (0.02) |
| | [-0.028] | [0.023] |
| *MarketCap* | -0.233*** | -0.498*** |
| | (0.036) | (0.037) |
| | [0.004] | [-0.064] |
| *Age* | -0.124*** | -0.058*** |
| | (0.012) | (0.017) |
| | [-0.023] | [0.004] |
| *Dividend* | -0.466*** | -0.72*** |
| | (0.12) | (0.108) |
| | [-0.026] | [-0.078] |
| *B/M* | -0.003 | 0.031*** |
| | (0.009) | (0.008) |
| | [-0.004] | [0.006] |
| *Price* | 0.084*** | 0.129*** |
| | (0.012) | (0.016) |
| | [0.005] | [0.014] |
| *Volatility* | -0.669*** | -0.837*** |
| | (0.135) | (0.16) |
| | [-0.061] | [-0.075] |
| *S&P 500* | 0.282*** | 0.03 |
| | (0.031) | (0.039) |
| | [0.064] | [-0.028] |
| *Return(t-3,t)* | 0.291*** | 0.303*** |
| | (0.039) | (0.036) |
| | [0.034] | [0.021] |
| *Return(t-12,t-3)* | 0.137*** | 0.149*** |
| | (0.022) | (0.022) |
| | [0.015] | [0.011] |
| *Leverage* | 0.377*** | -0.156** |
| | (0.053) | (0.07) |
| | [0.109] | [-0.074] |
| Number of institutions | 650 | |
| Number of unqiue stocks | 2,261 | |
| R-squared | 0.058 | |
| **Economic effects:** | | |
| Predicted probability at $\mu - \sigma$ | 0.469 | 0.281 |
| Predicted probability at $\mu - \sigma$ | 0.399 | 0.344 |
| Difference | -0.070 | 0.063 |

### 2.4.3 Robustness Tests

Our main analysis assumes that CEF investors examine CEF portfolio compositions and make the investment decisions accordingly. However, CEF investors may not be fully aware of all the stocks that CEFs invest in due to the investor inattention problem given that a typical CEF invests in 50 to 70 securities. Indeed, CEF investor attention might be limited to stocks that are most popular with CEFs. While a perfect solution to this problem is not possible as it requires researchers to read the investors' minds, a potential solution is to recast our analysis based on stocks that are obviously popular. For this purpose we target the most popular 30 securities held by CEFs; these make up 64.82% of the average CEF portfolio weighting.[15] As shown in Table 2.3, despite weaker economic significance, support for the liquidity-role provided by CEFs in portfolio delegation process persists. For a two standard deviation shock to the stock's illiquidity measure, there is a corresponding increase in the predicted probability of observing an indirect investment via a CEF by 3.7%, up from 7.4%. We also ensure that the observed results are not driven by a particular choice of illiquidity measure. As an alternative proxy, we also use the well-known Amihud (2002) illiquidity measure.[16] We define the Amihud measure for stock $i$ at month $t$ as follows:

$$Amihud_{i,t} = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_d|}{V_d},$$

where $R_d$ and $V_d$ are the return and volume of stock $i$ at day $d$. As before, we take their past 90-trading day average; i.e. $D = 90$.

[15] In unreported test we also study the top 20 securities held by the CEFs and the results are qualitatively the same.

[16] Goyenko et al. (2009) and Hasbrouck (2009) find that among the liquidity measures constructed from daily data, Amihud's is the best proxy for the high-frequency price impact measures of liquidity.

Table 2.3: Institutional investment choices - robustness tests.

This table provides two robustness tests on Table 2.2 results. The first robustness test repeats the estimation procedure in Table 2.2 but exclusively focusses on the top 30 holdings of the CEFs. The MNL model takes the following form:

$$\ln\left(\frac{P_{i,j,k}}{P_{i,0,k}}\right) = \beta_{0,j} + \beta_{1,j}\,EffectiveSpread_{i,k} + \beta_{2,j}\,MarketCap_{i,k} + \beta_{3,j}\,Age_{i,k} + \beta_{4,j}\,Dividend_{i,k} + \beta_{5,j}\,B/M_{i,k}$$
$$+\beta_{6,j}\,Price_{i,k} + \beta_{7,j}\,Volatility_{i,k} + \beta_{8,j}\,S\&P\ 500_{i,k} + \beta_{9,j}\,Return(t\text{-}3,t)_{i,k}$$
$$+\beta_{10,j}\,Return(t\text{-}12,t\text{-}3)_{i,k} + \beta_{11,j}\,Leverage_{i,k},$$

where $i = 1, 2, ..., I_k$ are the $i^{th}$ holding of institutional managers of $k = 1, 2, ...K$ and $j = 1, 2$ are the investment choices. We use $j = 0$ as the base category. In particular, we denote $j = 0$ as representing the outcome when stock $i$ is concurrently held by both CEF investors and CEFs, $j = 1$ when it is held only by CEF investors, and $j = 2$ when it is held only by CEFs. The second robustness test uses the Amihud (2002) illiquidity measure (*Amihud*), defined as the ratio of absolute daily return over the dollar trading volume, averaged over the past 90 trading days. Other control variables are as defined in Table 2.2. *EffectiveSpread* is the size-weighted relative effective spread, averaged over the past 90 trading days. *MarketCap*, expressed in millions of dollars, is the firm's equity value, calculated as the number of shares outstanding multiplied by the month-end closing stock price. *Age* is the number of months the firm first appeared in the CRSP. *Dividend*, *B/M*, and *Price* are the dividend yield, book-to-market ratio, and quarter-end price of the stock. *Volatility* is the standard deviation of daily stock returns measured over the past 24 months, expressed in percentage terms. $S\&P500$ is a binary variable that takes the value of one if the security is included in the S&P 500 membership and zero , otherwise. *Return(t-3,t)* and *Return(t-12,t-3)*, expressed in percentage terms, are the cumulative returns of the stock over the past three months and over the nine months preceding the beginning of filing quarter, respectively. *Leverage*, expressed in percentage terms, is total debt over total assets. We use the logarithmic of *EffectiveSpread*, *Amihud*, *MarketCap*, and *Age*. Year dummies are included in the models. All standard errors are clustered at the manager level and are shown in parentheses. The APEs are presented in square brackets. Number of institutional managers, number of unique stocks, and McFadden's $R$-squared are presented. For the MNL model, we also present the economic effects of *EffectiveSpread* on each of the predicted outcome. For example, to compute the economic effect of *EffectiveSpread* on direct investment, we add one standard deviation of *EffectiveSpread* to its mean and compute the predicted likelihood of observing direct investment using the estimated coefficients, holding all other control variables at their means. We also subtract the mean of *EffectiveSpread* by one standard deviation and compute the predicted likelihood of observing direct investment. We then compute the change in the predicted likelihood as the economic effect of *EffectiveSpread* on direct investment. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

- Continued on next page -

| Variables | Robustness test 1: top 30 holdings | | Robustness test 2: alternative illiquidity measure | |
|---|---|---|---|---|
| | **Direct investment vs. co-investment** | **Indirect investment vs. co-investment** | **Direct investment vs. co-investment** | **Indirect investment vs. co-investment** |
| *Constant* | 8.243*** | 6.273*** | 2.772*** | 3.721*** |
| | (0.558) | (0.577) | (0.383) | (0.425) |
| *EffectiveSpread (Amihud)* | -0.103*** | 0.105*** | -0.099*** | 0.129*** |
| | (0.014) | (0.021) | (0.019) | (0.022) |
| | [-0.022] | [0.014] | [-0.039] | [0.036] |
| *MarketCap* | -0.793*** | -0.658*** | -0.325*** | -0.345*** |
| | (0.05) | (0.055) | (0.04) | (0.047) |
| | [-0.077] | [0.002] | [-0.037] | [-0.025] |
| *Age* | -0.15*** | -0.103*** | -0.121*** | -0.06*** |
| | (0.013) | (0.018) | (0.011) | (0.017) |
| | [-0.016] | [0.002] | [-0.022] | [0.003] |
| *Dividend* | -2*** | -1.189*** | -0.52*** | -0.622*** |
| | (0.156) | (0.197) | (0.124) | (0.116) |
| | [-0.222] | [0.04] | [-0.051] | [-0.053] |
| *B/M* | 0.103*** | -0.051** | 0.002 | 0.022*** |
| | (0.015) | (0.025) | (0.009) | (0.008) |
| | [0.019] | [-0.01] | [-0.002] | [0.004] |
| *Price* | -0.003 | 0.143*** | 0.054*** | 0.174*** |
| | (0.011) | (0.022) | (0.011) | (0.013) |
| | [-0.009] | [0.01] | [-0.008] | [0.026] |
| *Volatility* | 2.714*** | -1.008*** | -1.129*** | -0.151 |
| | (0.249) | (0.34) | (0.161) | (0.172) |
| | [0.465] | [-0.241] | [-0.252] | [0.106] |
| *S&P 500* | 0.937*** | 0.136*** | 0.252*** | 0.027 |
| | (0.029) | (0.04) | (0.03) | (0.042) |
| | [0.13] | [-0.049] | [0.057] | [-0.025] |
| *Return(t-3,t)* | -0.047 | 0.56*** | 0.376*** | 0.164*** |
| | (0.053) | (0.056) | (0.043) | (0.044) |
| | [-0.042] | [0.043] | [0.07] | [-0.014] |
| *Return(t-12,t-3)* | 0.022 | 0.304*** | 0.158*** | 0.111*** |
| | (0.032) | (0.033) | (0.023) | (0.024) |
| | [-0.016] | [0.02] | [0.025] | [0.002] |
| *Leverage* | 0.818*** | -0.112 | 0.307*** | -0.062 |
| | (0.053) | (0.078) | (0.049) | (0.069) |
| | [0.128] | [-0.059] | [0.081] | [-0.048] |
| Number of institutions | 650 | | 650 | |
| Number of unique stocks | 2,259 | | 2,270 | |
| R-squared | 0.085 | | 0.059 | |
| **Economic effects:** | | | | |
| Predicted probability at $\mu - \sigma$ | 0.845 | 0.074 | 0.503 | 0.243 |
| Predicted probability at $\mu + \sigma$ | 0.793 | 0.111 | 0.291 | 0.463 |
| Difference | -0.052 | 0.037 | -0.212 | 0.220 |

As shown in Table 2.3, we continue to find that a stock's illiquidity is positively related to a manager's decision to outsource investment in the stock to a CEF. The estimated coefficient on the variable *Amihud* for indirect investment is 0.129 and is statistically significant at the 1% level. Moreover, the estimated economic magnitudes are large: the probability of observing an indirect investment increases from 24.3% to 46.3% for a two standard deviation change in *Amihud*, holding all other variables at their respective means. Taken together, our results are robust against sample selection issues or alternative illiquidity measures.

### 2.4.4 Heterogeneity Among CEF Investors

So far, our results do not disentangle institutional manager stock preferences related to illiquidity from other motives such as market segments, investment style, diversification, or discretion to deviate from benchmarks. The literature shows that managers' portfolio transaction costs are significantly related to their investment styles and turnover rates (Keim and Madhavan (1997) and Wermers (2000)). To address such issues we perform subsample analyses based on the institutions in the spirit of Bushee (1998, 2001). In particular, we re-estimate the MNL model in Equation (2.1) using sub-samples of our institutional investors based on the Bushee (1998, 2001) institutional classification schemes: turnover (transient, dedicated, or quasi-index) and investment style (large-cap growth, large-cap value, small-cap growth, and small-cap value).

Table 2.4: Institutional investment choices - subsample analysis by types of CEF investors.

This table presents the estimation results of Equation (2.1) for different types of CEF investors. Following Bushee (1998, 2001), we classify the CEF investors based on two different dimensions: turnover classification (transient, dedicated, and quasi-index) and style classification (large-cap growth, large-cap value, small-cap growth, and small-cap value). The MNL model takes the following form:

$$\begin{aligned}\ln\left(\frac{P_{i,j,k}}{P_{i,0,k}}\right) &= \beta_{0,j} + \beta_{1,j}\mathit{EffectiveSpread}_{i,k} + \beta_{2,j}\mathit{MarketCap}_{i,k} + \beta_{3,j}\mathit{Age}_{i,k} + \beta_{4,j}\mathit{Dividend}_{i,k} + \beta_{5,j}B/M_{i,k} \\ &\quad + \beta_{6,j}\mathit{Price}_{i,k} + \beta_{7,j}\mathit{Volatility}_{i,k} + \beta_{8,j}\mathit{S\&P\ 500}_{i,k} + \beta_{9,j}\mathit{Return(t\text{-}3,t)}_{i,k} \\ &\quad + \beta_{10,j}\mathit{Return(t\text{-}12,t\text{-}3)}_{i,k} + \beta_{11,j}\mathit{Leverage}_{i,k},\end{aligned}$$

where $i = 1, 2, ..., I_k$ are the $i^{th}$ holding of institutional managers of $k = 1, 2, ...K$ and $j = 1, 2$ are the investment choices. We use $j = 0$ as the base category. In particular, we denote $j = 0$ as representing the outcome when stock $i$ is concurrently held by both CEF investors and CEFs, $j = 1$ when it is held only by CEF investors, and $j = 2$ when it is held only by CEFs. *EffectiveSpread* is the size-weighted relative effective spread, averaged over the past 90 trading days. *MarketCap*, expressed in millions of dollars, is the firm's equity value, calculated as the number of shares outstanding multiplied by the month-end closing stock price. *Age* is the number of months the firm first appeared in the CRSP. *Dividend*, *B/M*, and *Price* are the dividend yield, book-to-market ratio, and quarter-end price of the stock. *Volatility* is the standard deviation of daily stock returns measured over the past 24 months, expressed in percentage terms. $S\&P500$ is a binary variable that takes the value of one if the security is included in the S&P 500 membership and zero , otherwise. *Return(t-3,t)* and *Return(t-12,t-3)*, expressed in percentage terms, are the cumulative returns of the stock over the past three months and over the nine months preceding the beginning of filing quarter, respectively. *Leverage*, expressed in percentage terms, is total debt over total assets. We use the logarithmic of *EffectiveSpread*, *MarketCap*, and *Age*. Year dummies are included in the models. All standard errors are clustered at the manager level and are shown in parentheses. The APEs are presented in square brackets. Number of institutional managers, number of unique stocks, and McFadden's $R$-squared are presented. For the MNL model, we also present the economic effects of *EffectiveSpread* on each of the predicted outcome. For example, to compute the economic effect of *EffectiveSpread* on direct investment, we add one standard deviation of *EffectiveSpread* to its mean and compute the predicted likelihood of observing direct investment using the estimated coefficients, holding all other control variables at their means. We also subtract the mean of *EffectiveSpread* by one standard deviation and compute the predicted likelihood of observing direct investment. We then compute the change in the predicted likelihood as the economic effect of *EffectiveSpread* on direct investment. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Investment choice | *EffectiveSpread* | Standard errors | APE | Number of institutions | Number of unique stocks | R-squared | Predicted probability at $\mu - \sigma$ | Predicted probability at $\mu + \sigma$ | Difference |
|---|---|---|---|---|---|---|---|---|---|---|
| **Turnover classification:** | | | | | | | | | | |
| Transient | Direct | -0.092*** | (0.025) | [-0.04] | 172 | 2,259 | 0.034 | 0.385 | 0.294 | -0.091 |
| | Indirect | 0.157*** | (0.039) | [0.042] | | | | 0.292 | 0.401 | 0.109 |
| Dedicated | Direct | 0.031 | (0.043) | [0.003] | 14 | 2,144 | 0.1 | 0.146 | 0.147 | 0.001 |
| | Indirect | 0.035 | (0.086) | [0.004] | | | | 0.609 | 0.622 | 0.013 |
| Quasi-index | Direct | -0.084*** | (0.017) | [-0.025] | 419 | 2,261 | 0.074 | 0.511 | 0.448 | -0.063 |
| | Indirect | 0.041 | (0.025) | [0.017] | | | | 0.261 | 0.308 | 0.047 |
| **Style classification:** | | | | | | | | | | |
| Large-cap growth | Direct | -0.036 | (0.03) | [-0.013] | 176 | 2,258 | 0.068 | 0.561 | 0.530 | -0.031 |
| | Indirect | 0.045 | (0.041) | [0.011] | | | | 0.169 | 0.194 | 0.025 |
| Large-cap value | Direct | -0.108*** | (0.024) | [-0.032] | 203 | 2,261 | 0.069 | 0.521 | 0.441 | -0.080 |
| | Indirect | 0.064* | (0.037) | [0.02] | | | | 0.200 | 0.252 | 0.052 |
| Small-cap growth | Direct | -0.062 | (0.046) | [-0.028] | 102 | 2,249 | 0.069 | 0.395 | 0.329 | -0.066 |
| | Indirect | 0.086 | (0.053) | [0.028] | | | | 0.394 | 0.468 | 0.074 |
| Small-cap value | Direct | -0.071*** | (0.023) | [-0.029] | 166 | 2,256 | 0.05 | 0.381 | 0.311 | -0.070 |
| | Indirect | 0.093*** | (0.031) | [0.031] | | | | 0.396 | 0.474 | 0.078 |

Table 2.4 summarizes the effects of illiquidity on the CEF investors' investment strategies. Although we include a full set of control variables as before, for brevity, we only report the coefficient estimates of *EffectiveSpread*, standard errors, APEs, and indicators of economic significance. We note that on the basis of turnover classification, quasi-indexers are the main CEF investors (numbering 419), followed by transient investors (172), and dedicated investors (14). Transient or short-term investors, characterized by having high portfolio turnover, are more likely to invest in CEFs compared to dedicated investors and exhibit distinct asymmetric investment behavior. The estimated APEs are largest among the three (0.042 as compared to 0.004 for dedicated investors and 0.017 for quasi-indexers). Economically, our results suggest that a two standard deviation change around the mean of *EffectiveSpread* increases the predicted likelihood of transient investors not investing in the stock directly by 10.9%. The results are consistent with expectations, since it may not be optimal for transient investors to invest directly in illiquid securities due to their constant high demand for liquidity and portfolio rebalancing needs. While the coefficient estimates for *EffectiveSpread* remain statistically significant for the quasi-indexers and transient investors, this is not the case for the dedicated investors. Moreover, dedicated investors do not need CEFs to gain exposure to illiquid securities, since the number of such CEF investors is relatively small, 14 in total. The results suggest that CEFs do not play a vital role in the portfolio compositions of dedicated institutional investors. Rather than outsourcing investments in illiquid securities to CEFs, they generally opt for direct investments. An alternative explanation would be that such investors typically have high portfolio concentration and low turnover, suggesting they adopt a long-term investment strategy. Since their investment horizons are typically longer than those of transient investors and quasi-indexers, immediate demand for liquidity is low, allowing them to invest in such stocks directly. Taken together, the results show that an additional advantage of investing in CEFs is that they can afford to hold illiquid stocks over longer horizons than the average institutional investor. Institutional investors seem to value this additional dimension.

Our next classification method is based on institutional investment styles. From Table 2.4, there are 176 large-cap growth-oriented investors, 203 large-cap value-oriented investors, 102 small-cap growth-oriented investors, and 166 small-cap value-oriented investors. Two notable patterns emerge. First, small-cap institutions are more likely to outsource illiquid investments to their underlying CEFs. For small-cap institutional investors, the coefficient *EffectiveSpread* enters the model at significance level of 10% or better but appears to be either marginally significant or insignificant for large-cap institutional investors. Moreover, the economic influences of *EffectiveSpread* are more pronounced on investment decisions made by small-cap institutions than large-cap institutions. For instance, a two standard deviation increase in *EffectiveSpread* increases the probability of small-cap growth-oriented investors choosing indirect investments by 7.4%, compared to a 2.5% increase in the case of large-cap growth-oriented investors. We attribute this finding to the investment environment the small-cap investors operate in, which is typically characterized by large trading costs. Second, we also observe value-oriented managers are more sensitive to liquidity issues than growth-oriented managers, especially for small-cap value-oriented institutions. This makes sense as value stocks are typically less liquid than growth stocks (Watanabe and Watanabe (2008), Akbas et al. (2010) for further evidence). In terms of magnitudes, we observe that a two standard deviation change around the mean of *EffectiveSpread* leads to an increase of 7.8% of observing an indirect investment, which is economically significant. Overall, these observed patterns are largely consistent with the CSS theory's implications.

### 2.4.5 Is the Liquidity Advantage from the Closed-End Nature?

Our next step is to provide additional evidence that it is indeed the closed end nature of CEFs that delivers the liquidity advantage suggested by our results so far. Ideally, to compare our closed-end investment vehicles with open-ended funds, we would need to repeat our tests on a comparable set of equity mutual funds. Unfortunately, since mutual funds are not traded on exchanges as stocks, in the way CEFs are, they are not contained in regulatory filings of portfolio holdings. Even where institutional investors have exposure to mutual funds, our ideal experiment is not possible, as we cannot observe mutual funds in the portfolios of institutional investors.[17] Instead, motivated by the observation that a subset of equity funds, small cap mutual funds, has a mandate to invest in illiquid stocks that we can observe, we repeat our tests focusing only on this small cap sub-sample.

Prior research shows that the open-end structure of the mutual fund industry exposes it to liquidity risks. Chen et al. (2004) and Yan (2008) show that fund returns decline with fund size especially for small-cap oriented funds, attributing their results to liquidity factors. Theoretically, Chen et al. (2010) also model the destabilizing fund flow implications of opened-end fund structures and conclude that this vulnerability is a consequence of the liquidity of open-end funds' underlying assets. Other related studies include Chordia (1996) and Nanda et al. (2000), who highlight the role of mutual fund loads in deterring investor outflows. We take advantage of this liquidity vulnerability of mutual funds to provide additional evidence that it is the closed end feature of CEFs that delivers the liquidity benefits we have demonstrated

[17] At the end of each calendar quarter, the SEC provides a list of reportable securities for portfolio holdings filings known as the Official List of Section 13(f) Securities. These securities primarily include U.S. exchange-traded stocks, shares of closed-end investment companies, shares of exchange-traded funds, certain convertible debt securities, equity options, and warrants. Shares of open-end investment companies i.e. mutual funds, should not be reported on Form 13F (see Question 7 of Division of Investment Management: Frequently Asked Questions About Form 13F. Available at `https://www.sec.gov/divisions/investment/13ffaq.htm`).

in this paper. We treat the sub-sample of small-cap funds and our CEFs as two representative investor samples by aggregating their respective ownership of stocks. Our conjecture is that while both types of funds invest in small-cap securities, small-cap mutual funds are more likely to be sensitive towards liquidity risks and not demonstrate the same liquidity provision advantages as CEFs. We use a regression model of the determinants of CEF or small-cap mutual fund holdings that takes the following form:

$$
\begin{aligned}
IO_{MF,i,t}(IO_{CEF,i,t}) \quad = \quad & \beta_0 + \beta_1 \mathit{EffectiveSpread}_{i,t} + \beta_2 \mathit{MarketCap}_{i,t} + \beta_3 \mathit{Age}_{i,t} \\
& + \beta_4 \mathit{Dividend}_{i,t} + \beta_5 \mathit{B/M}_{i,t} + \beta_6 \mathit{Price}_{i,t} + \beta_7 \mathit{Volatility}_{i,t} \\
& + \beta_8 \mathit{S\&P\ 500}_{i,t} + \beta_9 \mathit{Return(t\text{-}3,t)}_{i,t} + \beta_{10} \mathit{Return(t\text{-}12,t\text{-}3)}_{i,t} \\
& + \beta_{11} \mathit{Leverage}_{i,t} + \epsilon_i, \qquad (2.2)
\end{aligned}
$$

where $IO_{i,t,SG}$ ($IO_{i,t,CEF}$) is the aggregate ownership of small-cap mutual funds (CEFs) in stock $i$ at quarter $t$.[18] Our hypothesis is that stock ownership by CEFs (small-cap funds) will be increasing (decreasing) with stock illiquidity as measured by effective spread. We employ two widely used econometric models in the literature: the Fama and Macbeth (1973) approach as in Gompers and Metrick (2001) and the firm fixed-effects panel-regression approach.

Table 2.5 shows the results using the Fama and Macbeth (1973) approach. Here, we run a series of cross-sectional regressions for each quarter (30 quarters in total). Since the estimated coefficients for each quarter are not independent across time, we do not report any time-series statistics other than the average coefficient. Instead, we report the number of positive and negative estimates that are statistically significant at the 5% level or better. To improve our inference, we use White (1980) heteroscedasticity-

[18] We obtain the small-cap mutual funds holdings data from CRSP Mutual Fund Database (MFDB) and Thomson Reuters using MFLINKS. According to the Lipper classification code, a small-cap equity mutual fund is one with either “SCCE", “SCGE", or “SCVE".

robust standard errors in our regressions. Controlling for other stock characteristics, small-cap mutual funds have a tendency to tilt towards stocks that are more liquid in nature. Out of 30 quarterly estimates, 26 coefficient estimates on *EffectiveSpread* of them are negatively significant at the 5% level or better. This is in sharp contrast to the case for CEFs, where 20 of the total estimated coefficients on *EffectiveSpread* are positively significant. In their investing in small-cap stocks, it appears CEFs tilt towards more illiquid securities, while open-ended small-cap mutual funds favor more liquid securities.

Similar conclusions can be reached when we employ the firm fixed-effects regression with time dummies. To account for possible dependency structure in the residuals, the standard errors are clustered at the firm-level. Under this approach, we find that *EffectiveSpread* enters the model with a statistically significant coefficient of $-0.308$ for the small-cap mutual fund ownership and 0.023 for the CEF ownership. Overall, the results suggest that closed-end structure is best suited for funds investing in illiquid securities.

Table 2.5: Comparison between small-cap mutual funds and CEFs.

This table presents the estimation results of Equation (2.2). The regression model takes the following form:

$$\begin{aligned} IO_{i,MF}(IO_{i,CEF}) &= \beta_0 + \beta_1 \mathit{EffectiveSpread}_i + \beta_2 \mathit{MarketCap}_i + \beta_3 \mathit{Age}_i + \beta_4 \mathit{Dividend}_i + \beta_5 B/M_i \\ &\quad + \beta_6 \mathit{Price}_i + \beta_7 \mathit{Volatility}_i + \beta_8 \mathit{S\&P\ 500}_i + \beta_9 \mathit{Return(t\text{-}3,t)}_i \\ &\quad + \beta_{10} \mathit{Return(t\text{-}12,t\text{-}3)}_i + \beta_{11} \mathit{Leverage}_i + \epsilon_i, \end{aligned}$$

where the dependent variable $IO_{i,MF}$ is the total ownership of small-cap mutual funds in stock $i$ and $IO_{i,CEF}$ is the total ownership of CEFs in stock $i$. *EffectiveSpread* is the size-weighted relative effective spread, averaged over the past 90 trading days. *MarketCap*, expressed in millions of dollars, is the firm's equity value, calculated as the number of shares outstanding multiplied by the month-end closing stock price. *Age* is the number of months the firm first appeared in the CRSP. *Dividend*, *B/M*, and *Price* are the dividend yield, book-to-market ratio, and quarter-end price of the stock. *Volatility* is the standard deviation of daily stock returns measured over the past 24 months, expressed in percentage terms. *S&P*500 is a binary variable that takes the value of one if the security is included in the S&P 500 membership and zero , otherwise. *Return(t-3,t)* and *Return(t-12,t-3)*, expressed in percentage terms, are the cumulative returns of the stock over the past three months and over the nine months preceding the beginning of filing quarter, respectively. *Leverage*, expressed in percentage terms, is total debt over total assets. We use the logarithmic of *EffectiveSpread*, *MarketCap*, and *Age*. Year dummies are included in the models. All standard errors are clustered at the manager level and are shown in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| | **Fama-Macbeth regression** | | **Panel regression** | |
|---|---|---|---|---|
| | **Small-cap** | **CEF** | **Small-cap** | **CEF** |
| *Constant* | 6.029 | 1.114 | 6.011*** | 1.548*** |
| | [25,0] | [28,0] | (0.740) | (0.189) |
| *EffectiveSpread* | -1.88 | 0.098 | -0.308*** | 0.023*** |
| | [1,26] | [20,0] | (0.034) | (0.007) |
| *MarketCap* | -0.942 | -0.199 | -0.293*** | -0.237*** |
| | [2,23] | [0,30] | (0.085) | (0.035) |
| *Age* | -0.436 | 0.1 | -0.209* | 0.000 |
| | [3,20] | [25,0] | (0.125) | (0.028) |
| *Dividend* | -12.65 | 1.369 | -0.991* | 0.136 |
| | [0,27] | [8,0] | (0.550) | (0.144) |
| *B/M* | -0.226 | 0.108 | 0.022 | 0.004 |
| | [0,15] | [13,0] | (0.042) | (0.010) |
| *Price* | 1.678 | 0.198 | 1.662*** | 0.218*** |
| | [30,0] | [28,0] | (0.109) | (0.043) |
| *Volatility* | -15.9 | -0.157 | -2.894*** | 0.019 |
| | [0,30] | [0,0] | (0.624) | (0.148) |
| *S&P 500* | -8.069 | 0.142 | -4.753*** | 0.104*** |
| | [0,30] | [16,0] | (0.267) | (0.035) |
| *Return(t-3,t)* | -0.503 | 0.027 | -0.942*** | 0.018 |
| | [3,11] | [1,0] | (0.073) | (0.020) |
| *Return(t-12,t-3)* | -0.62 | -0.008 | -0.471*** | -0.019* |
| | [1,13] | [0,0] | (0.038) | (0.011) |
| *Leverage* | -1.849 | 0.197 | -0.763*** | 0.037 |
| | [0,24] | [13,0] | (0.293) | (0.059) |
| R-squared | 0.265 | 0.174 | 0.21 | 0.121 |

### 2.4.6 Evidence from the U.K. CEF Industry

This subsection extends our analysis to the U.K. investment trust or CEF industry. According to the AIC, the trade body for CEFs in the U.K., as of December 2014 the industry held assets under management estimated to be £121 billion. This figure corresponds to 15% of the open-end funds in the U.K. Moreover, the U.K. CEF industry consists of mainly equity funds, generally divided into domestic equity, foreign equity, venture capital trusts, and others.[19] Importantly, unlike the U.S. CEF industry which is dominated by retail investors, two-thirds of the shares in the U.K. CEFs are on average held by institutional investors. Figure 2.2(a) presents the institutional ownership of U.K. CEFs in December of each year from 2003 to 2013. Consistent with industry statistics, institutional ownership in the CEF industry is fairly stable over the years, ranging between 60% and 70% in recent years. Similar patterns can be observed in Figure 2.2(b) when we break down the U.K. CEF sample by investment category.[20]

[19]Available at `http://www.theaic.co.uk/` and `http://www.theinvestmentassociation.org/`, respectively.

[20]See Dimson and Minio-Kozerski (1999) for a more elaborated comparison between the U.S. and U.K. CEF industry.

Figure 2.2: Institutional ownership of U.K. CEFs.

Figure 2.2(a)

This figure presents the average institutional ownership of all categories of CEFs used in the sample in December of each calendar year. The sample period spans from 2003 to 2012.

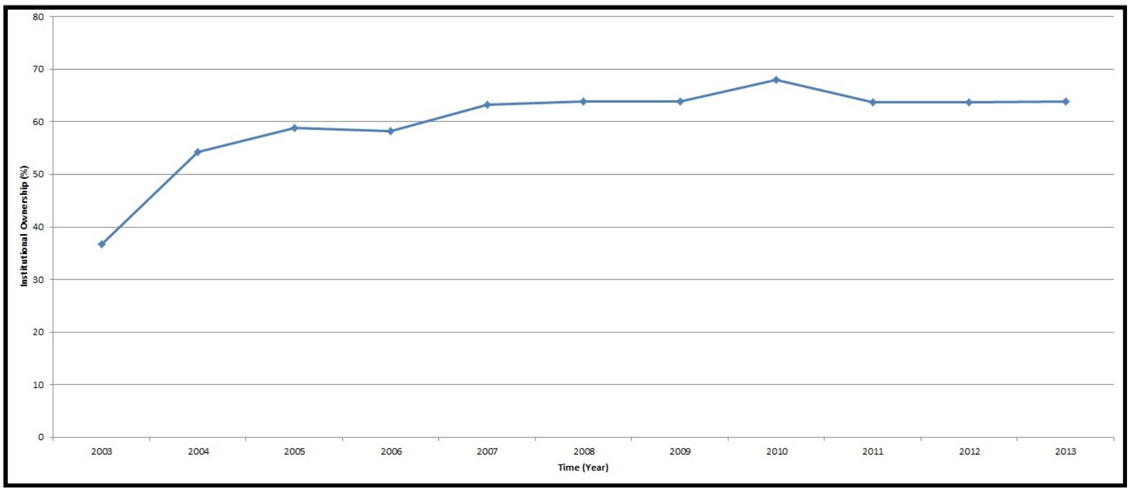
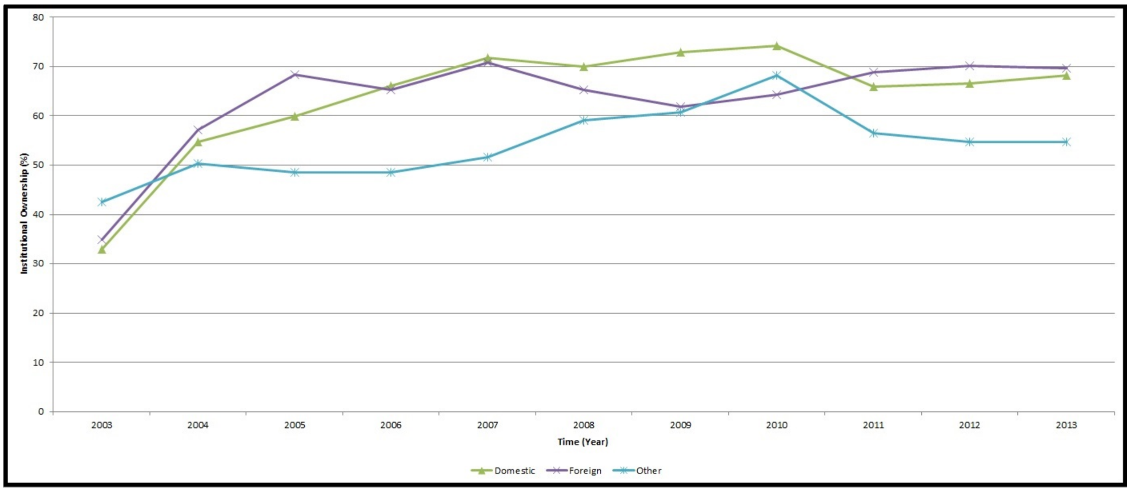



Figure 2.2(b)

This figure presents the average institutional ownership of different categories of CEFs in December of each calendar year. The sample period spans from 2003 to 2012. We categorize investment trusts into domestic equity CEFs, foreign equity CEFs, and others.



We replicate our main results using the newly assembled U.K. data, focusing on the investment decisions made by 376 U.K. institutional managers who invest in at least one domestic equity CEF. The unconditional probabilities of observing co-investment, direct investment, and indirect investment are 44.82%, 21.41%, and 33.76%. In the absence of intraday tick data, we use the Amihud (2002) measure as a proxy for stock's illiquidity. Other security variables are defined as in Section 2.3 above.

Table 2.6 presents the estimation results. Over the entire sample period, we again find that the illiquidity of a stock has a positive influence on the fund manager's decision to opt for indirect investment via the CEFs, a result that closely resembles our U.S. analysis. At the same time, we also observe an institutional manager is also more likely to invest directly into illiquid stocks. The estimated coefficient *Amihud* for the direct and indirect investment equation are 0.059 and 0.085, respectively, which are both statistically significant at the 1% level. However, in terms of economic magnitude, a two standard deviation increase on *Amihud* changes the implied probability of outsourcing by 8.9%, which is much larger than the increase in implied probability of direct investment (estimated to be 2.6%). This result is still consistent with the CSS theory's implication, leading us to conclude that the liquidity-based theory holds outside of the U.S. market.

Table 2.6: Institutional investment choices - U.K. evidence.

This table presents the evidence using the U.K. sample. The MNL model takes the following form:

$$\ln\left(\frac{P_{i,j,k}}{P_{i,0,k}}\right) = \beta_{0,j} + \beta_{1,j}\,Amihud_{i,k} + \beta_{2,j}\,MarketCap_{i,k} + \beta_{3,j}\,Age_{i,k} + \beta_{4,j}\,Dividend_{i,k} + \beta_{5,j}\,B/M_{i,k}$$
$$+\beta_{6,j}\,Price_{i,k} + \beta_{7,j}\,Volatility_{i,k} + \beta_{8,j}\,S\&P\ 500_{i,k} + \beta_{9,j}\,Return(t\text{-}3,t)_{i,k}$$
$$+\beta_{10,j}\,Return(t\text{-}12,t\text{-}3)_{i,k} + \beta_{11,j}\,Leverage_{i,k},$$

where $i = 1, 2, ..., I_k$ are the $i^{th}$ holding of institutional managers of $k = 1, 2, ...K$ and $j = 1, 2$ are the investment choices. We use $j = 0$ as the base category. In particular, we denote $j = 0$ as representing the outcome when stock $i$ is concurrently held by both CEF investors and CEFs, $j = 1$ when it is held only by CEF investors, and $j = 2$ when it is held only by CEFs. *Amihud* is the Amihud (2002) illiquidity measure, defined as the ratio of absolute daily return over the dollar trading volume, averaged over the past 90 trading days. *MarketCap*, expressed in millions of dollars, is the firm's equity value, calculated as the number of shares outstanding multiplied by the month-end closing stock price. *Dividend*, $B/M$, and *Price* are the dividend yield, book-to-market ratio, and quarter-end price of the stock. $Volatility$ is the standard deviation of daily stock returns measured over the past 24 months, expressed in percentage terms. $Return(t-3,t)$ and $Return(t-12,t-3)$, expressed in percentage terms, are the cumulative returns of the stock over the past three months and over the nine months preceding the beginning of filing quarter, respectively. *Leverage*, expressed in percentage terms, is total debt over total assets. We use the logarithmic of *Amihud*, *MarketCap*, and *Age*. Year dummies are included in the models. All standard errors are clustered at the manager level and are shown in parentheses. The APEs are presented in square brackets. Number of institutional managers, number of unique stocks, and McFadden's $R$-squared are presented. For the MNL model, we also present the economic effects of *Amihud* on each of the predicted outcome. For example, to compute the economic effect of *Amihud* on direct investment, we add one standard deviation of *Amihud* to its mean and compute the predicted likelihood of observing direct investment using the estimated coefficients, holding all other control variables at their means. We also subtract the mean of *Amihud* by one standard deviation and compute the predicted likelihood of observing direct investment. We then compute the change in the predicted likelihood as the economic effect of *Amihud* on direct investment. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

- Continued on next page -

| **Variables** | **Direct investment vs. co-investment** | **Indirect investment vs. co-investment** |
|---|---|---|
| *Constant* | -0.033 | -0.007 |
| | (0.118) | (0.164) |
| *Amihud* | 0.059*** | 0.085*** |
| | (0.011) | (0.009) |
| | [0.004] | [0.014] |
| *MarketCap* | -0.079*** | -0.021 |
| | (0.019) | (0.021) |
| | [-0.012] | [0.001] |
| *Dividend* | 2.113*** | 1.338*** |
| | (0.337) | (0.263) |
| | [0.269] | [0.136] |
| *B/M* | -0.068*** | 0.026*** |
| | (0.01) | (0.009) |
| | [-0.013] | [0.01] |
| *Price* | 0.089 | 0.389 |
| | (0.239) | (0.301) |
| | [-0.012] | [0.076] |
| *Volatility* | 0.107*** | 0.023* |
| | (0.01) | (0.012) |
| | [0.017] | [-0.003] |
| *Return(t-3,t)* | 0.003 | 0.009 |
| | (0.033) | (0.029) |
| | [0] | [0.002] |
| *Return(t-12,t-3)* | 0.023 | 0.107*** |
| | (0.022) | (0.017) |
| | [-0.003] | [0.021] |
| *Leverage* | -0.476*** | 0.081* |
| | (0.048) | (0.045) |
| | [-0.087] | [0.05] |
| Number of institutions | 376 | |
| Number of unique stocks | 335 | |
| R-squared | 0.013 | |
| **Economic significance:** | | |
| Predicted probability at $\mu - \sigma$ | 0.199 | 0.271 |
| Predicted probability at $\mu + \sigma$ | 0.225 | 0.360 |
| Difference | 0.026 | 0.089 |

## 2.5 Conclusion

This paper is the first to investigate the extent to which the liquidity-based theory proposed by CSS explains investor demand for CEFs. Conditional on an institutional manager investing in CEFs, we find that such institutions are more likely to avoid securities that are already held by the CEFs, which are observed to more illiquid. Such patterns vary across institutions, depending on their investment horizons. We show that our findings are also generalizable to the U.K., suggesting they are applicable to other markets with significant CEF industries.

More broadly, our findings at least partially provide justification for the usage of investment fund structures that are closely related to CEFs such as secondary market traded hedge funds, REITs, and listed private equities. Viewing such structures through a liquidity lens may prove fruitful for future empirical and theoretical research.

## 2.6 Appendix: Description of Variables

This table contains a list of variables described in Section 2.3. The variables are sourced from the following databases: CRSP, Compustat, CRSP/Compustat merged, Compustat Global, Morningstar, and Trade and Quote (TAQ).

| **Notation** | **Variable name** | **Description** | **Data sources** |
|---|---|---|---|
| *CEF Premium* | CEF share price premium | The monthly premium on a CEF, computed as the ratio of its month-end closing share price to its NAV, and expressed in percentage terms. | Morningstar/Compustat |
| *CEF TNA* | TNA of CEF | The TNA of the CEF investment portfolio, calculated as the market value of the CEF's equity divided by the CEF share price premium, and expressed in millions of dollars. | Morningstar/Compustat |
| *CEF GrossExp* | CEF gross expense ratio | Total gross expenses (net expenses with waivers added back in) divided by the fund's average net assets, expressed as a percentage. | Morningstar |
| *CEF Turnover* | CEF turnover | The CEF portfolio turnover, obtained by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets, expressed in percentage terms. | Morningstar |
| *EffectiveSpread* | Relative value-weighted effective spread measure | The daily relative value-weighted effective spread measure, calculated as two times the absolute difference between transaction price and mid-point price, weighted by the size of the trade. This measure is then averaged over the past 90 trading days. | TAQ |
| *Amihud* | Amihud (2002) illiquidity measure | The ratio of absolute daily return over the dollar trading volume, averaged over the past 90 trading days. | CRSP |
| *MarketCap* | Market value of firm equity | The number of shares outstanding of the firm multiplied by the stock month-end closing price, expressed in millions of dollars. Both the numerator and denominator are split-adjusted using the cumulative factor to adjust price (CFACPR) and cumulative factor to adjust shares (CFACSHR). | CRSP/Compustat Global |
| *Age* | Firm's age | The number of months since the firm first appeared in the CRSP database. | CRSP/Compustat Global |
| *Dividend* | Dividend yield | Dividends (CS#21) over the market value of firm equity, expressed in percentage terms. | CRSP/Compustat Merged/Compustat Global |

- Continued on next page -

| Notation | Variable name | Description | Data sources |
|---|---|---|---|
| *B/M* | Book-to-market ratio | Shareholder equity equals, in order, stockholder equity (CS#144), total common equity plus preferred stock par value (CS#60 + CS#130), or total assets minus total liabilities plus minority interest (CS#6 - CS#181 + CS#38). We then subtract shareholder equity from the preferred stock value , using redemption (CS#56), liquidating (CS#10), or carrying value (CS#130), in that order, if available, to obtain the book equity. Finally, the book-to-market ratio is computed by taking the ratio between the firm's book equity value and market capitalization . | CRSP/Compustat Merged/Compustat Global |
| *Price* | Price | The month-end price of the firm, adjusted for stock-splits. | CRSP/Compustat Global |
| *Volatility* | Stock return volatility | Volatility calculated as the standard deviation of monthly stock returns over the past 24-months, expressed in percentage terms. | CRSP/Compustat Global |
| *S&P500* | S&P 500 | A binary variable that takes the value of one if the firm is included in the S&P 500 composite index and zero otherwise. | CRSP/Compustat Merged/Compustat Global |
| *Return(t-3,t)* | Cumulative stock return over the past three months | A firm's cumulative return in the previous filing quarter, expressed in percentage terms. | CRSP/Compustat Global |
| *Return(t-12, t-3)* | Cumulative stock return over the nine months preceding the beginning of filing quarter | A firm's cumulative return the three quarters preceding the previous filing quarter, expressed in percentage terms. | CRSP/Compustat Global |
| *Leverage* | Leverage | Ratio of debt (CS#34 + CS#9) to total assets (CS#6), expressed in percentage terms. | CRSP/Compustat Merged/Compustat Global |

# Chapter 3

# How Informed Are Hedge Fund Option Strategies?

## 3.1 Abstract

We employ a comprehensive disclosure set of hedge fund option strategies and examine their performances. Our study outcome offers no affirmation of hedge fund speculation skills. A liquid quarterly tracking portfolio of options earns significant negative returns ranging between $-1.59\%$ and $-0.89\%$ per month. These results are robust to assumptions on option moneyness, time-to-maturity, performance evaluation methodologies, and stock characteristics. We also reveal that there is little performance differential between hedge funds and other institutional investors. Taken together, our results do not indicate that current views on hedge funds are skilled in using options to speculate.

## 3.2 Introduction

> *"The seminal work of Black and Scholes (1973) and Merton (1973) generated an explosion of research into methods for computing theoretical option prices and hedge ratios. By contrast, more than three decades after the beginning of listed option trading much less is known about the trading of this important class of securities."* (Lakonishok et al. (2007) p. 813)

How options are traded is a subject of widespread interest. Theoretical works by both Black (1975) and Easley et al. (1998) predict informed investors are more likely to trade in the options market to take advantage of the embedded leverage and liquidity features of options. Building on the preceding notions, a growing literature presents evidence on how various market participants engage in options trading and the related impact on portfolio performance. These studies span different types of investors, including mutual funds (Koski and Pontiff (1999), Deli and Varma (2002), Almazan et al. (2004), Fong et al. (2005), Frino et al. (2009), Cici and Palacios (2015), Natter et al. (2015)), hedge funds (Chen (2011), Aragon and Martin (2012)), and retail investors (Bauer et al. (2009)). However, there is no conclusive evidence on this topic to date, due to either the use of seemingly different data sources or empirical methodologies. For instance, Chen (2011) finds no material evidence that hedge funds' use of derivative securities is associated with superior fund performance. In contrast, Aragon and Martin (2012) show hedge fund option holdings can predict both future stock returns and volatility, leading to the conclusion that hedge funds are skilled in using options for speculative purposes. In this paper, we target the hedge fund industry and provide additional evidence on whether hedge funds' long option positions show skill in speculating about the underlying stocks.

We assemble a large sample of 932 hedge fund managers and extract their option holdings directly from 13F filings for the period between 1999 and 2012. Using a performance evaluation approach aimed directly at their options trading strategies, we infer hedge fund managers' skills at the individual hedge fund firm level. For each manager, on a monthly basis, we form a tracking portfolio of options based on their previous quarter-end's disclosed option positions. Using assumptions about option strike prices and time-to-maturity, we form the tracking portfolios using short-term at-the-money (ATM) options, defined, following Christoffersen et al. (2014) and Xing and Zhang (2013), as options whose time-to-maturity is between 45 and 90 days and absolute delta is between 0.4 and 0.6. Empirically, these option contracts are both liquid and actively traded in the exchange. Over the whole sample period, we find negative median tracking portfolio monthly returns of $-1.483\%$ for the bull strategies, $-1.765\%$ for the bear strategies, and $-1.244\%$ for the straddle strategies. We also stress test our results by varying the options' time-to-maturity and moneyness assumptions in forming the tracking portfolios but find no material evidence in support of managerial speculative skills.

Next, we implement an alternative performance evaluation approach at the aggregate industry level. We focus on all hedge funds' option holdings at the end of each quarter, effectively treating the entire hedge fund industry as one giant investor (for similar applications in the mutual fund industry, see Chen et al. (2000), Gompers and Metrick (2001), Griffin and Xu (2009)). Our results show a tracking portfolio formed based on the aggregate hedge fund option holdings earns significant negative monthly return of between $-1.588\%$ and $-0.877\%$ per month, depending on the specific option strategies. Chen et al. (2000) show mutual fund manager's buy trades outperform their sell trades, as proxied by the quarterly changes in their reported holdings. Thus, it is plausible that managerial investment skills are better captured by their trade decisions instead of their passive holdings.[1] Adopting a

[1]Subsequent studies utilize better datasets that capture the granularity of managers' trade

similar approach as in Chen et al. (2000), however, we find no evidence in support of the above conjecture. A tracking portfolio formed based on positive changes in option holdings does not outperform a tracking portfolio formed based on negative changes in option holdings.

We conduct additional robustness tests. First, we control for hedge fund investment preferences. Griffin and Xu (2009) show hedge funds generally prefer small, opaque value securities compared to mutual funds. Thus, we examine whether hedge fund managers are skilled in using options to speculate in different segments of the market by dividing their option holdings into different subgroups based upon the underlying stock's characteristics. Next, we test whether or not these managers' option holdings contain private information for the next quarter earnings events. Ali et al. (2004), Ke and Petroni (2004), Yan and Zhang (2009), Baik et al. (2010), and others find that changes in institutional manager holdings can predict subsequent earnings announcement abnormal returns. In this regard, we carry out an event study based approach and assess the returns achieved by these option strategies during various earnings announcement windows. Lastly, we compare the performance of these hedge fund option holdings with other institutional investors. If hedge fund managers are deemed more sophisticated in using options to speculate, we should at least observe greater degree of outperformance in hedge fund options compared to other institutional investors. These further tests show similar insignificant evidence of hedge fund option investment capabilities across all cases.

Our paper joins the abundance literature on hedge fund performance research. In one strand, Ackermann et al. (1999), Brown et al. (1999) suggest hedge funds deliver at least some abnormal returns. On the other, Asness et al. (2001), Amin and Kat

decisions. For instance, Puckett and Yan (2011) examine the institutional managers' interim trading skills and conclude such managers' trades earn significant abnormal returns and tend to persist over time.

(2003), and Kat and Palaro (2006) find that hedge funds do not deliver alpha. More recently, using 13F hedge fund holdings, Griffin and Xu (2009) also conclude there is little differential ability between hedge funds and mutual funds. While both Aragon and Martin (2012) and ours contribute to the literature by examining performance of hedge fund option holdings, ours differ in two dimensions. First, we alleviate the issue of self-reporting biases in hedge fund databases as documented in Aiken et al. (2012) and Agarwal et al. (2013a). Second, for inference purposes, instead of tracking the returns of option's underlying stocks as in Aragon and Martin (2012), we directly construct hypothetical copycat option portfolios to investigate the performance of these hedge funds' option positions as discussed.

More importantly, the overarching evidence presented in this paper emphatically shows these hedge funds' disclosed option positions do not depict the story of informed trading as suggested in Black (1975) or Easley et al. (1998). The puzzle, then, is that if these option positions generate negative returns, why the hedge fund managers do not reverse the positions and make money? A plausible explanation is that hedge fund managers could be using these option positions to hedge against their short positions in the spot market.[2] Evidence in favor of this conjecture can be found in Chen (2011), who observes hedge funds that use derivatives tend to have lower fund risks, engage in less risk-shifting, and are less likely to be liquidated.

The rest of the chapter is organized into three sections. Section 3.3 describes the data. Section 3.4 examines the performance of hedge fund option strategies. Section 3.5 concludes.

[2]For instance, while a hedge fund manager can profit from a fall in the stock price by shorting the stock, this strategy is subject to an unlimited loss should the stock price begins to rise. As such, the manager who has sold stock short would hedge his/her position by purchasing a call option on the underlying, which can be used to guard against unexpected adverse losses. By SEC regulatory requirements, however, hedge funds and other money managers are not required to disclose their short position, if they have any. Hence, it is not possible to gain insights into that spectrum of space.

## 3.3 Data

### 3.3.1 Institutional Holdings

Section 13(f) of the Securities Exchange Act of 1934 mandates that all institutional investment managers who exercise investment discretion over \$100 million or more are legally required to report the details of holdings of more than $\$200,000$ or $10,000$ shares using Form 13F. Past researchers often accessed this ownership information via data vendors such as Thomson Reuters and CDA/Spectrum. One major limitation is that these data only contain long institutional equity positions.

According to the U.S. Securities Exchange and Commission (SEC), managers are also required to report option positions if the options themselves are securities in the Official List of 13(f) Securities for that quarter. In light of this data incompleteness, we directly extract institutional option positions from the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. Given that Form 13F was not generally available in the early years of EDGAR database, we restrict our sample to be between 1999:Q1 and 2012:Q3. There are 139,264 Form 13Fs filed over the sample period.[3]

Based on Form 13F's reporting format, we implement a series of computer algorithms to extract the relevant option positions by locating keywords such as "CALL" and "PUT". For each observation, we obtain the following information: (1) the issuer/security's name, (2) the security's CUSIP number, (3) the notional value of the options (in thousands of dollars), (4) the quantity held, and (5) the type of option (call or put).[4] In total there are $1,839,387$ option positions, of which $951,352$

[3] The filings can be accessed via the following website: `http://www.sec.gov/edgar/searchedgar/ftpusers.htm`.

[4] While the managers should consider only the value of such options for \$100 million thresholds, they must report the market value and quantity in terms of the underlying securities. Readers are referred to the Division of Investment Management of SEC who provides a list of comprehen-

are call options and 888,035 are put options. Institutional managers can report on behalf of several funds operating under the family umbrella. Thus, it is possible to observe multiple positions on an exact same security. We aggregate these multiple option positions at the manager level for each date-security-call/put combination. This is consistent with Thomson Reuters' approach in compiling their institutional equity positions.

Next, we merge the option positions and the Thomson Reuters equity positions. For each manager name appearing in the SEC EDGAR database, we identify the corresponding manager in the Thomson Reuters database. We use a combination of an algorithm name-matching technique and a manual screening process.[5] This gives us 3,104 unique institutional investors together with their complete portfolio allocation decisions between stocks and options. For ease of exposition, we hereafter refer to this merged ownership database as 13F/Thomson Reuters.[6] At this stage, we note that the SEC does not require managers to disclose options' strike price and time-to-maturity. While these limitations are undesirable, we discuss the steps taken to address them in Section 3.4.

### 3.3.2 Hedge Fund Classifications

Since regulatory constraints are not uniformly imposed across institutions, it is important for us to control for investor heterogeneity issues. For instance, hedge funds display several unique features that distinguish them from other institutional

sive frequently asked questions about form 13F in `http://www.sec.gov/divisions/investment/13ffaq.htm`.

[5]For instance, Thomson Reuters contains a manager called "T.H. Fitzgerald and Company." (MGRNO = 38250) whereas the corresponding manager in the EDGAR database is "Fitzgerald Thomas H JR /CT/" (CIK = 1019509). Upon checking the holdings from both the Thomson Reuters and the original SEC filings, we confirm that these two seemingly different institutions are indeed the same.

[6]Using the same data source, Agarwal et al. (2013b) has 3,134 unique institutional managers in their sample for the period between 1999 and 2007.

managers. These include flexible investment strategies (e.g., short selling, leverage, derivative trading), strong managerial incentives (e.g., compensation structure and a high watermark feature), and an opaque information environment. In a similar spirit of Agarwal et al. (2013a) and Shive and Yun (2013), to identify hedge fund managers from the 13F/Thomson Reuters database, we rely on three hedge fund commercial databases, those of the Lipper's Trading Advisor Selection System, Hedge Fund Research, and Morningstar. These databases contain records of individual hedge fund names and their management companies. For each disclosed management company, we look up the corresponding institutional manager from the 13F/Thomson Reuters database. However, as pointed out by Agarwal et al. (2013a), these commercial databases are subject to self-reporting biases and hence may not reflect the hedge fund industry universe. For instance, hedge funds may self-select themselves into one of the reporting databases to advertise their funds to clients. Likewise, funds could also choose not to be entered in a database to conceal their profitable trading strategies from the public.

We mitigate the issue of self-reporting bias by using information in Form ADV in our hedge fund identification process. We follow past literature to classify a manager as a hedge fund if more than 50% of its clients are high-net-worth individuals or other pooled investment vehicles and it imposes a performance-based fee on its clients.[7] In addition, we eliminate hedge funds that have a side-by-side mutual fund business or are affiliated with banks.[8] This yields a final sample of 932 unique "pure

[7]These information are located in Form ADV under Question D(2) and E of Item 5: Information About Your Advisory Business. As pointed by Jame (2014), the Form ADVs contain information of nearly all investment advisors including hedge funds as required by the Dodd-Frank Act starting in March 2012. Such mandatory nature is essential to minimize any form of selection bias in our hedge funds sample. Form ADVs are available to download at `http://www.adviserinfo.sec.gov/IAPD/Content/Search/iapd_Search.aspx`.

[8]By analyzing a sample of management firms that simultaneously run both hedge funds and mutual funds, Cici et al. (2010) show that these mutual funds generally underperform their peers, suggesting management firms may strategically transfer performance from mutual funds to hedge funds

play" hedge funds, a number that is sufficiently close to what is reported in past studies (Agarwal et al. (2013a)). The remaining non-hedge fund institutional manager sample primarily consists of commercial banks, insurance companies, mutual fund management companies, asset management companies, investment banks, brokers, private wealth management companies, pension funds, endowments, and so on.

### 3.3.3 Hedge Fund Summary Statistics

Table 3.1 shows the summary statistics of our hedge funds sample and the prevalent role that options play in these managers' portfolio allocation strategies. The number of hedge fund managers increases from 204 in 1999 to 871 in 2012. In any quarter, we define a hedge fund manager as an option user if the manager discloses at least one option position in his or her portfolio. The percentage of hedge funds that trade in the options market increases substantially over the years, approaching 30% in 2012. The total number of hedge fund option positions relative to their total portfolio positions ranges between 6.84% and 19.49%.

Our 13F/Thomson Reuters database also provides a rich framework on how hedge fund managers formulate their option investment strategies in conjunction with the underlying equity holdings. In particular, we can classify any option positions held by investors into one of the following six distinct type of strategies: (1) a call only position; (2) a simultaneous holding of both stock and call positions; (3) a put only position; (4) a simultaneous holding of both call and put positions; (5) a simultaneous holding of stock, call, and put positions; and (6) a simultaneous holding of stock and put positions.

Following Aragon and Martin (2012), we group these option strategies into four categories: (1) bull, (2) bear, (3) protective put, and (4) straddle. We classify the observed option position as a bull strategy if the manager reports a call option with or without an existing equity position, a bear strategy if the manager reports a put option only, a protective put strategy if the manager reports a put option with an existing equity position, and a straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. Table 3.1 reveals that volatility speculation strategies such as straddles are the most popular among hedge fund managers: Approximately 5% of total portfolio positions are initiated as straddles. This is followed by bull strategies and protective put strategies. Bear strategies (pure put option strategies) are the least popular among managers.

As mentioned earlier, although the absence of further information on the option's strike price and time-to-maturity precludes us to compute the option holdings value relative to the total portfolio value, we can use an option's rational bound to estimate the maximum exposure a manager has in the options market. It is well-known from basic option pricing theory that a call option's value is worth no more than the underlying stock and a put option is worth no more than its strike price. If a manager discloses a call position, we use the call option's underlying stock price as the maximum value the call option can attain. Similarly, if a manager discloses a put position, we use the maximum strike price of the option class (i.e. the set of all put options for the stock) as the maximum value the put option can attain. Information on all exchange-traded equity options, including prices and returns are obtained from OptionMetrics. We report the time series median of the estimated maximum option exposure across all managers. Table 3.1 shows that a typical hedge fund's estimated maximum exposure to the options market is only 12.87%. Overall, the summary statistics suggest hedge fund option usage and exposure are rather low.

Table 3.1: Hedge fund managers and their option positions.

This table reports, for each year, the number of hedge fund managers, percentage of managers who disclosed at least one option position, and average percentage of option positions in the manager's overall portfolio holdings. We also categorize the manager's option positions into different option strategies and report the corresponding percentage. Following Aragon and Martin (2012) strategy classifications, for each quarter and each manager's option position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; bear strategy if the manager reports a put option only; protective put strategy if the manager reports a put option with an existing equity position; and, straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. We use an option's rational bounds to estimate a manager's maximum exposure to the options market, defined as the ratio of option position value over the total portfolio value. If a manager discloses a call position, we use the call option's underlying stock price as the maximum value the call option can attain. Similarly, if a manager discloses a put position, we use the maximum strike price of the option class (i.e. the set of all the put options for the stock) as the maximum value the put option can attain. We report the time series median of the estimated maximum option exposure across all managers. The sample period is from 1999:Q1 to 2012:Q3.

| **Year** | **Number** | **Option user (%)** | **Option holdings (%)** | **Bull (%)** | **Bear (%)** | **Protective put (%)** | **Straddle (%)** | **Estimated maximum option exposure (%)** |
|---|---|---|---|---|---|---|---|---|
| 1999 | 204 | 2.45 | 6.84 | 2.40 | 0.07 | 1.88 | 2.49 | 3.46 |
| 2000 | 252 | 6.35 | 7.18 | 2.22 | 0.11 | 2.08 | 2.76 | 3.52 |
| 2001 | 265 | 6.42 | 7.69 | 2.33 | 0.34 | 2.06 | 2.96 | 2.89 |
| 2002 | 315 | 7.30 | 12.62 | 4.11 | 0.65 | 3.29 | 4.58 | 3.79 |
| 2003 | 372 | 6.99 | 13.75 | 4.00 | 0.92 | 1.89 | 6.94 | 5.26 |
| 2004 | 429 | 11.89 | 12.98 | 3.38 | 1.77 | 3.93 | 3.91 | 6.96 |
| 2005 | 515 | 17.86 | 12.98 | 4.21 | 2.41 | 3.32 | 3.04 | 7.76 |
| 2006 | 609 | 17.73 | 14.72 | 4.17 | 1.82 | 4.34 | 4.40 | 10.28 |
| 2007 | 708 | 21.89 | 14.92 | 4.55 | 1.98 | 4.23 | 4.15 | 9.52 |
| 2008 | 774 | 25.97 | 19.49 | 5.94 | 2.18 | 5.70 | 5.66 | 10.51 |
| 2009 | 793 | 22.82 | 17.27 | 5.16 | 1.85 | 4.92 | 5.34 | 11.63 |
| 2010 | 827 | 26.48 | 17.46 | 4.80 | 2.03 | 4.89 | 5.75 | 11.83 |
| 2011 | 883 | 26.95 | 16.40 | 4.51 | 2.15 | 4.78 | 4.96 | 13.21 |
| 2012 | 871 | 28.36 | 15.81 | 4.51 | 2.26 | 4.20 | 4.84 | 12.87 |

## 3.4 Performance of Hedge Fund Option Strategies

### 3.4.1 Individual Hedge Fund Option Holdings and Returns

In this section, we empirically investigate whether hedge fund managers are informed traders in the options market. For a start, we follow a common approach in the performance evaluation method and form a tracking portfolio of options based on a manager's option holdings. Since it is not compulsory for hedge fund managers to reveal their options' strike prices and time-to-maturity, we overcome this issue by imposing certain assumptions on our portfolio formation process.

As an example, we illustrate how to form the tracking portfolio on hedge fund bull strategies (i.e., long call position) but similar procedures apply to hedge fund bear strategies. At the beginning of each month and for each manager, we form a hypothetical short-term ATM call option portfolio based on the manager's last quarter-end 13F disclosure. To be included in this option portfolio, the call option's time-to-maturity must be between 45 and 90 days and its absolute delta must be between 0.4 and 0.6 at the beginning of each formation month. The second condition is the definition of ATM options, in line with past studies.[9] We use the reported market value of these call option positions (i.e. the product of option prices and the number of option holdings) to construct manager-specific portfolio weights. We then track the monthly raw returns of these tracking portfolios of all hedge fund managers over the subsequent months. It is noted, though, that the asymmetric nature of options leads to returns that are decidedly not normally distributed. We therefore report the time series median of these tracking portfolios across all hedge

[9]Both short-term and ATM options are the most liquid and actively traded by market participants. In unreported tabulation, we observe approximately 78% of options traded have a maturity of less than three months. Using intraday option prices, Christoffersen et al. (2014) estimate that out-of-the-money (OTM) options have the highest effective spreads, followed by ATM options and in-the-money (ITM) options. According to their estimates, effective spreads for OTM options could be twice as large as ATM options, on average.

fund managers. We use the non-parametric one-sample sign test to assess whether the reported median returns are significantly different from zero. Unlike the $t$-test, sign test is known to be robust to both non-normality and non-symmetric distributional assumptions.

Table 3.2: Performance of quarterly tracking portfolio of options for hedge fund's directional option strategies.

This table reports the median returns of quarterly tracking portfolio of options on individual hedge funds quarter-end directional option strategies. The sample period is between 1999:Q1 and 2012:Q3. Panel A and B report results for portfolios that track the hedge fund's bull and bear strategies, respectively. Following Aragon and Martin (2012) strategy classifications, for each quarter and each manager's option holding position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; and bear strategy if the manager reports a put option only. At the beginning of each month, we form a short-term ATM tracking portfolio of options based on manager's last quarter-end bull strategies. This portfolio includes all call options whose maturity is between 45 and 90 days and absolute delta is between 0.4 and 0.6 at the beginning of that month. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the individual manager's portfolio weights. We track the monthly raw returns of these weighted portfolios over the subsequent months. We report the time series of the median raw return across all hedge fund managers. We also report the median raw return for a medium-term ATM and long-term ATM tracking portfolio of options. Medium-term ATM (long-term ATM) tracking portfolio is formed using call options whose maturity is between 91 and 135 (136 and 180) days and absolute delta is between 0.4 and 0.6. In the last two columns, we report the results for portfolios that are long stocks underlying reported bull option holdings as in Aragon and Martin (2012). Here, quarterly reported underlying notional values of option holdings for bull is used to construct manager portfolios of the underlying common stock. Monthly raw returns and performance of these portfolios are generated over the subsequent months. We also compute the DGTW characteristic-based benchmark-adjusted return for these portfolios. Similar procedures apply in constructing the tracking portfolios of options based on hedge fund's bear strategies, as reported in Panel B. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

- Continued on next page -

| Panel A: Bull | | | | | |
|---|---|---|---|---|---|
| **Year** | **Short-term** | **Medium-term** | **Long-term** | **Stock** | **DGTW** |
| 1999 | -2.829* | -0.221 | -1.607 | 0.503 | 0.27 |
| 2000 | -7.162*** | -0.175 | -2.469*** | -1.721 | -0.717 |
| 2001 | -2.535** | -0.431 | -0.736 | 1.086 | 0.435 |
| 2002 | -3.718*** | -1.433*** | -1.711*** | -1.713*** | 0.527 |
| 2003 | 0.294 | 0.661* | 1.954*** | 1.569*** | 0.385* |
| 2004 | -0.715** | -0.002 | 0.719** | 0.838*** | -0.142 |
| 2005 | -1.396*** | -0.141* | -0.175 | 0.516** | -0.218 |
| 2006 | -1.153*** | -0.154** | 0.39** | 0.943*** | 0.111 |
| 2007 | -2.533*** | -0.186*** | -0.491*** | -0.991*** | -0.342*** |
| 2008 | -4.256*** | -0.98*** | -2.08*** | -3.328*** | -0.146 |
| 2009 | 0.711*** | 0.574*** | 3.462*** | 4.203*** | 1.295*** |
| 2010 | -0.299 | 0.404*** | 0.88*** | 1.686*** | -0.469*** |
| 2011 | -1.81*** | -0.104* | -0.777*** | -0.03 | -1.42*** |
| 2012 | -1.561*** | -0.222** | 0.205 | 0.29 | 2.49*** |
| 1999-2006 | -1.522*** | -0.158*** | 0.103 | 0.641*** | -0.015 |
| | (14.418) | (12.107) | (15.459) | (8.399) | (6.946) |
| 2007-2012 | -1.785*** | -0.11*** | 0 | 0.536*** | 0.002 |
| | (13.588) | (12.836) | (17.202) | (12.427) | (10.509) |
| 1999-2012 | -1.722*** | -0.121*** | 0.014 | 0.575*** | -0.003 |
| | (13.763) | (12.69) | (16.847) | (11.631) | (9.804) |

| Panel B: Bear | | | | | |
|---|---|---|---|---|---|
| **Year** | **Short-term** | **Medium-term** | **Long-term** | **Stock** | **DGTW** |
| 1999 | -1.963 | -0.588 | -1.09 | -0.092 | 3.745 |
| 2000 | 1.87 | 3.975 | 5.096 | -8.558* | -1.24 |
| 2001 | -2.157* | -0.709** | 0.53 | -1.844 | -3.164 |
| 2002 | -0.518 | 0.249 | 0.829** | -3.212*** | -0.675 |
| 2003 | -3.185*** | -0.64*** | -1.2*** | 2.847*** | 1.392** |
| 2004 | -1.773*** | -0.08 | -0.706*** | 0.227 | -0.443 |
| 2005 | -1.966*** | -0.45*** | -0.522** | 0.599* | -0.125 |
| 2006 | -1.797*** | -0.358*** | -0.32 | 0.37 | -0.138 |
| 2007 | 0.074 | 0.11** | 1.636*** | -2.478*** | -1.805*** |
| 2008 | 0.268 | 0.346** | 2.633*** | -5.887*** | -1.37*** |
| 2009 | -4.402*** | -1.335*** | -3.035*** | 4.479*** | 1.4*** |
| 2010 | -3.327*** | -0.949*** | -1.461*** | 1.816*** | -0.361 |
| 2011 | -1.971*** | -0.391*** | -0.004 | -0.59* | -1.899*** |
| 2012 | -1.385*** | -0.441*** | -0.756*** | -0.435 | 2.879*** |
| 1999-2006 | -1.992*** | -0.303*** | -0.444*** | 0.395** | -0.149 |
| | (10.283) | (10.585) | (12.94) | (10.17) | (8.993) |
| 2007-2012 | -1.856*** | -0.386*** | -0.34*** | -0.225 | -0.487*** |
| | (10.698) | (9.347) | (14.229) | (13.427) | (11.647) |
| 1999-2012 | -1.894*** | -0.366*** | -0.365*** | -0.001 | -0.382*** |
| | (10.617) | (9.62) | (13.972) | (12.743) | (11.067) |

Panel A of Table 3.2 reports the baseline results. With the exception in 2009, a quarterly tracking portfolio of short-term ATM options on hedge fund bull strategies generates either insignificant returns or significant negative monthly returns in all years. Over the whole sample period, the tracking portfolio returns $-1.722\%$ per month. In the next two columns, we modify our tracking portfolio formation procedures: We use ATM call options but with a longer time-to-maturity. For the medium-term (long-term) ATM tracking portfolio, we include all ATM call options whose maturity is between 90 and 135 (136 and 180 days). Although the underperformance is reduced, a medium-term ATM tracking portfolio still earns a negative monthly return of $-0.121\%$. The median returns from a long-term ATM tracking portfolio, on the other hand, are not materially different from zero. In Panel B, the outcomes for a quarterly tracking portfolio of options on hedge fund bear strategies are even more dismal. For instance, a long-term ATM option portfolio yields significant negative monthly returns of $-0.365\%$. Taken together, our results hardly suggest evidence on hedge fund superior managerial speculative skills in the options market.

For completeness, we replicate the results documented in Aragon and Martin (2012). As in ours, in their paper, the authors use the disclosed option positions to form a stock portfolio for each hedge fund manager each quarter. Specifically, in a bullish tracking portfolio, the stock's portfolio weight equals the market value underlying the call positions on that stock divided by the aggregated market value underlying all reported call positions. Similarly, in a bearish portfolio the stock's portfolio weight equals the market value underlying the put positions on that stock divided by the aggregated market value underlying all reported put positions. We follow their approach and report the median bullish tracking stock portfolio returns in Panel A of Table 3.2. Consistent with Aragon and Martin (2012), we observe this tracking bullish portfolio is able to generate significant positive raw returns of 0.575% per month. While the tracking bearish portfolio is insignificant (Table 3.2 Panel B), the 0.576% difference is highly significant (not tabulated). In the last column we decompose the performance of these tracking stock portfolios as in DGTW. The characteristic-adjusted measures for the bullish and bearish stock portfolio are $-0.003\%$ and $-0.382\%$ per month, respectively, and the difference of $-0.379\%$ is highly significant, in line with the findings by Aragon and Martin (2012).

Although the use of stock portfolios in Aragon and Martin (2012) bypasses the issue of unobservable options' strike price and time-to-maturity in the data, we argue such an approach inevitably overlooks many features that uniquely pertain to options. On one hand, since options are inherently leveraged securities, an increase (decrease) in the underlying stock price should increase the call (put) option value by a larger percentage. The implication of this statement is that we should observe a similar (or stronger) result if one forms a tracking option portfolio instead of a tracking stock portfolio. On the other hand, the nature of decaying time value component embedded in most options implies that option holders will lose money on average, *ceteris paribus*. The tracking option portfolio will perform worse than the tracking stock portfolio if the stock price remains about the same. While it is not clear which of these opposing forces will dominate on an ex-ante basis, empirically from the results in Table 3.2, we observe the quarterly tracking option portfolios of all maturities inevitably struggle against the ravages of time.

Next, we examine the extent to which the results documented in Table 3.2 are influenced by the choice options' moneyness assumptions. Let $\Delta$ be the option's hedge ratio. In additional to ATM options, we define four other moneyness groups: (1) DOTM where $|\Delta| \in [0, 0.2)$; (2) OTM where $|\Delta| \in [0.2, 0.4)$; (3) ITM where $|\Delta| \in (0.6, 0.8]$; and (4) deep-in-the-money (DITM) where $|\Delta| \in (0.8, 1]$. Together with the previous three categories of option's maturity, we construct a total of 15 quarterly tracking portfolio of options based on hedge fund option strategies. We report the results in Table 3.3. Overall, we contend that our baseline conclusions are not significantly affected by the choice of option moneyness. With the exception of long-term ITM and DITM tracking portfolios, we observe all other bullish tracking portfolios generate significant negative monthly returns. Perhaps, even worst, none of the 15 bearish tracking portfolios demonstrates hedge fund managers' speculative skills in a downside market.

Table 3.3: Performance of quarterly tracking portfolio of options on hedge fund's directional option strategies - moneyness assumptions.

This table reports the median returns of quarterly tracking portfolio of options on individual hedge funds quarter-end directional option strategies. The sample period is between 1999:Q1 and 2012:Q3. Panel A and B report results for portfolios that track the hedge fund's bull and bear strategies, respectively. Following Aragon and Martin (2012) strategy classifications, for each quarter and each manager's option holding position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; and bear strategy if the manager reports a put option only. Let $|\Delta|$ be the option's hedge ratio. We divide the option's moneyness into 5 groups: DOTM where $|\Delta| \in [0, 0.2)$; out-of-the-money (OTM) where $|\Delta| \in [0.2, 0.4)$; ATM where $|\Delta| \in [0.4, 0.6]$; ITM where $|\Delta| \in (0.6, 0.8]$; and DITM where $|\Delta| \in (0.8, 1]$. For each of this moneyness group, at the beginning of each month, we form a short-term tracking portfolio of options based on manager's last quarter-end bull strategies. For instance, a short-term DOTM tracking portfolio of options includes all call options whose maturity is between 45 and 90 days and $|\Delta| \in [0, 0.2)$ at the beginning of that month. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the individual manager's portfolio weights. We track the monthly raw returns of these weighted portfolios over the subsequent months. We report the median raw return across all hedge fund managers. We also report the median raw return for a medium-term ATM and long-term ATM tracking portfolio of options. Medium-term ATM (long-term ATM) tracking portfolio is formed using call options whose maturity is between 91 and 135 (136 and 180) days and absolute delta is between 0.4 and 0.6. Similar procedures apply in constructing the tracking portfolios of options based on hedge fund's bear strategies, as reported in Panel B. Standard deviations of portfolio returns are reported in parentheses. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| **Panel A: Bull** | | | |
|---|---|---|---|
| **Moneyness** | **Short-term** | **Medium-term** | **Long-term** |
| DOTM | -1.824*** | -0.386*** | -0.384*** |
| | (44.502) | (54.632) | (44.433) |
| OTM | -2.383*** | -0.284*** | -0.199*** |
| | (20.713) | (18.023) | (24.632) |
| ATM | -1.722*** | -0.121*** | 0.014 |
| | (13.763) | (12.69) | (16.847) |
| ITM | -0.869*** | 0 | 0.132*** |
| | (8.282) | (7.652) | (11.799) |
| DITM | -0.55*** | 0 | 0.03* |
| | (5.96) | (5.326) | (6.921) |
| **Panel B: Bear** | | | |
| **Moneyness** | **Short-term** | **Medium-term** | **Long-term** |
| DOTM | -3.19*** | -1.176*** | -1.626*** |
| | (23.566) | (27.278) | (23.835) |
| OTM | -2.735*** | -0.645*** | -0.837*** |
| | (17.321) | (18.617) | (18.223) |
| ATM | -1.894*** | -0.366*** | -0.365*** |
| | (10.617) | (9.62) | (13.972) |
| ITM | -1.219*** | -0.193*** | -0.172*** |
| | (49.251) | (8.421) | (10.42) |
| DITM | -0.762*** | -0.211*** | -0.201*** |
| | (7.334) | (5.684) | (6.603) |

An additional advantage of using exchange-traded options to form the tracking portfolio is that we can investigate the hypothetical returns generated from mimicking hedge fund straddles strategies. Unlike directional strategies such as bull and bear strategies, straddles stand to earn the most should the underlying stock price unexpectedly move by a large magnitude. To see whether hedge fund straddle strategies are profitable, we first retain all paired call and put options that share the same time-to-maturity and strike price. We apply the same steps as in Table 3.2 to construct the short-term ATM quarterly tracking portfolios of the options for each manager each quarter. We report the time series median of the portfolio returns in Table 3.4. The short-term ATM option portfolio earns median raw returns of $-1.265\%$ per month from 1999:Q1 to 2012:Q3. Similar conclusions can be reached when we look at medium- and long-term ATM option portfolios, albeit with a slight improvement in returns. The bottom line is that we interpret this evidence as against the assertion that hedge fund managers are skilled in volatility speculation activities.

Table 3.4: Performance of quarterly tracking portfolio of options on hedge fund's straddle option strategies.

This table reports the median returns of quarterly tracking portfolio of options on individual hedge funds quarter-end straddle option strategies. The sample period is between 1999:Q1 and 2012:Q3. Following Aragon and Martin (2012) strategy classifications, for each quarter and each manager's option holding position, we classify the observed option position as straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. At the beginning of each month, we form a short-term ATM tracking portfolio of options based on manager's last quarter-end straddle strategies. We retain all paired call and put option that share the same time-to-maturity and strike price. This portfolio includes all paired call and put options whose maturity is between 45 and 90 days, and absolute delta is between 0.4 and 0.6 at the beginning of that month. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the individual manager's portfolio weights. We track the monthly raw returns of these weighted portfolios over the subsequent months. We report the time series of the median raw return across all hedge fund managers. We also report the median raw return for a medium-term ATM and long-term ATM tracking portfolio of options. Medium-term ATM (long-term ATM) tracking portfolio is formed using call options whose maturity is between 91 and 135 (136 and 180) days and absolute delta is between 0.4 and 0.6. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| **Year** | **Short-term** | **Medium-term** | **Long-term** |
|---|---|---|---|
| 1999 | -0.884 | 0.914 | 0.262 |
| 2000 | -0.558 | 0.038 | 0.505 |
| 2001 | -1.192*** | -0.134 | -0.182 |
| 2002 | -1.366*** | -0.156* | -0.409* |
| 2003 | -1.275*** | -0.062 | -0.441*** |
| 2004 | -1.188*** | -0.194* | -0.42** |
| 2005 | -1.079*** | -0.175** | -0.403*** |
| 2006 | -0.95*** | -0.099 | -0.081 |
| 2007 | -0.723*** | -0.076* | 0.225 |
| 2008 | -1.104*** | -0.103** | -0.032 |
| 2009 | -1.716*** | -0.271*** | -0.983*** |
| 2010 | -1.31*** | -0.237*** | -0.56*** |
| 2011 | -1.645*** | -0.208*** | -0.109 |
| 2012 | -1.724*** | -0.245*** | -0.811*** |
| 1999-2006 | -1.099*** | -0.094*** | -0.269*** |
| | (5.22) | (3.731) | (4.554) |
| 2007-2012 | -1.366*** | -0.187*** | -0.359*** |
| | (7.163) | (6.284) | (8.209) |
| 1999-2012 | -1.265*** | -0.168*** | -0.336*** |
| | (6.776) | (5.776) | (7.523) |

### 3.4.2 Robustness Test 1: Aggregate Hedge Fund Holdings and Trading

In this section, we implement the performance evaluation approach used in Chen et al. (2000) with mutual funds. At the beginning of each month, we aggregate the option holdings for each underlying stock across all hedge fund managers according to their last quarter-end disclosed option strategies. For each strategy, we form a short-term ATM option portfolio and track the return earned from following these hedge fund aggregate positions. This approach naturally reflects the overall opinion or consensus of the hedge fund industry on their option investments.

As in the previous section, the individual position's weight within the portfolio are based on the reported market value of option holdings at the beginning of each month. This will give us a time series return of the portfolio over 55 quarters or 165 monthly returns. We report the median returns and utilize a sign test for statistical testing purposes. We repeat the portfolio construction process using both medium-term ATM and long-term ATM options.

Table 3.5: Performance of hedge fund option strategies - an aggregate approach.

This table reports the median returns of quarterly tracking portfolio of options based on aggregate hedge funds quarter-end option strategies using Chen et al. (2000) approach. The sample period is between 1999:Q1 and 2012:Q3. Following Aragon and Martin (2012) strategy classifications, for each quarter and manager's option holding position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; bear strategy if the manager reports a put option only; protective put strategy if the manager reports a put option with an existing equity position; and, straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. At the end of each quarter, we compute the aggregate hedge funds' option positions for each stock according to the strategy classifications. To illustrate, in Panel A, at the beginning of each month, we form a short-term ATM tracking portfolio of options based on last quarter-end bull strategies of all managers. This portfolio includes all call options whose maturity is between 45 and 90 days and absolute delta is between 0.4 and 0.6 at the beginning of that month. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the portfolio weights. We track the monthly raw returns of these weighted portfolios over the subsequent months. We report the median raw return across all months. We also report the median raw return for a medium-term ATM and long-term ATM tracking portfolio of options. Medium-term ATM (long-term ATM) tracking portfolio is formed using call options whose maturity is between 91 and 135 (136 and 180) days and absolute delta is between 0.4 and 0.6. This procedure applies similarly to bear, protective put, and straddle strategies. In Panel B, we assess whether the bull and bear results in Panel A are robust against moneyness assumptions. Let $|\Delta|$ be the option's hedge ratio. We divide the option's moneyness into 5 groups: DOTM where $|\Delta| \in [0, 0.2)$; out-of-the-money (OTM) where $|\Delta| \in [0.2, 0.4)$; ATM where $|\Delta| \in [0.4, 0.6]$; ITM where $|\Delta| \in (0.6, 0.8]$; and DITM where $|\Delta| \in (0.8, 1]$. For each of this moneyness group, at the beginning of each month, we form a short-term tracking portfolio of options based on manager's last quarter-end bull or bear strategies. We track the monthly raw returns over the subsequent months and report the median return. In Panel C, we form a short-term quarterly tracking portfolio of options based on hedge funds net trading positions. For each quarter-end and each disclosed option position, we compute the net change in the number of contracts held by hedge funds from the previous quarter. If the net change is positive we assign this position to the buy portfolio, otherwise we assign it to the sell portfolio. We then compute the buy-and-hold returns on these two trade portfolios by mimicking the changes in number of contracts during each quarter using long positions only. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. A Wilcoxon two-sample test is used to test whether the returns between the buy portfolio and sell portfolio are significantly different from each other. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

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If hedge fund managers have option selectivity skills, then stock option strategies widely used by managers should earn positive returns; otherwise we should observe insignificant or even negative relation between the returns and hedge fund option holdings. Panel A of Table 3.5 presents the median returns of our aggregate holding-based approach. The quarterly tracking portfolio of options generates significant negative returns across all strategy types. For example, a buy-and-hold bear strategy portfolio returns $-1.241\%$ per month and it is statistically significant at the 5% level. On the other hand, a buy-and-hold straddle strategy portfolio generates $-0.887\%$ per month. In addition, we report the standard deviations of portfolio returns in brackets. Consistent with intuition, option returns are highly volatile. For instance, the estimated returns volatility for a short-term bullish portfolio is 6% per month. These results cannot be explained by the choice of moneyness assumptions we impose

| **Panel A: Holding-based approach** | | | |
|---|---|---|---|
| **Strategy** | **Short-term** | **Medium-term** | **Long-term** |
| Bull | -1.411** | 0.191 | 2.362*** |
| | (5.993) | (5.144) | (6.563) |
| Bear | -1.241** | -0.021 | 0.591 |
| | (4.312) | (8.139) | (6.605) |
| Protective Put | -1.588*** | -0.136 | 0.01 |
| | (4.334) | (3.182) | (5.184) |
| Straddle | -0.887*** | -0.02 | 0.058 |
| | (1.693) | (1.772) | (2) |
| **Panel B: Moneyness assumptions** | | | |
| **Strategy** | **Moneyness** | **Return** | **Standard Deviation** |
| Bull | DOTM | -0.937* | (16.287) |
| | OTM | -1.575** | (7.777) |
| | ATM | -1.411** | (5.99) |
| | ITM | -0.637* | (3.761) |
| | DITM | -0.508*** | (2.958) |
| Bear | DOTM | -2.729*** | (8.999) |
| | OTM | -1.998*** | (6.303) |
| | ATM | -1.241** | (4.312) |
| | ITM | -0.924** | (4.452) |
| | DITM | -0.785*** | (3.526) |
| **Panel C: Trading-based approach** | | | |
| **Strategy** | **Buy** | **Sell** | **Buy-minus-sell** |
| Bull | -1.247 | -0.685** | -0.562 |
| | (9.507) | (6.407) | |
| Bear | -1.019** | -1.185*** | 0.166 |
| | (4.192) | (5.272) | |
| Protective Put | -1.649*** | -1.676*** | 0.027 |
| | (4.604) | (4.595) | |
| Straddle | -0.946*** | -0.891*** | -0.055 |
| | (2.003) | (2.28) | |

on the tracking option portfolios as evidenced in Table 3.5, Panel B, in which we present the case for both bullish and bearish option strategies.

Chen et al. (2000) advocate the formation of tracking portfolios based on manager trades. They argue trades reflect a stronger managerial view on the market compared to passive holding decisions and, hence, are better at capturing managerial investment abilities more succinctly. Intuitively, portfolios that track manager's buy decisions (i.e., where the net change in an option position from that in the previous quarter is positive) should outperform portfolios that track manager's sell decisions (i.e., where the net change in an option position from that in the previous quarter is negative). A similar approach has also been adopted by Yan and Zhang (2009) and Baik et al. (2010), among others. To this end, we construct two separate portfolios: a buy portfolio and a sell portfolio. For each quarter-end and each disclosed option position, we compute the net change in the number of contracts held by hedge funds from the previous quarter. If the net change is positive, we assign this position to the buy portfolio; otherwise, we assign it to the sell portfolio.

We then compute the buy-and-hold returns on these two trade portfolios by mimicking the changes in number of contracts during each quarter using only long positions. Under this approach, if hedge fund managers possess superior trading skills, we expect newly purchased options to outperform and newly sold or closed out options do not. The opposite of our expectation is for there to be no relation between option returns and trade direction, that is, no substantial return differentiation between the buy and sell portfolios. A non-parametric Wilcoxon two-sample test is used to gauge the statistical significance of the results.

Panel C of Table 3.5 indicates no substantial evidence of performance differentiation between the buy and sell portfolios. For instance, across all option strategies and time-to-maturity categories, the differences in returns between the buy and sell portfolios are not significantly different from zero. We do not detect any material performance differentiation between the two portfolios.

### 3.4.3 Robustness Test 2: Subsample Analyses

We conduct a battery of additional checks in the subsequent sections. First, we make sure our results are not affected by hedge fund investment preferences. For example, Griffin and Xu (2009) document that, unlike mutual funds, hedge funds generally prefer smaller and opaque value securities. We build on the methodology outlined in the previous section but divide our sample of firms along four dimensions: (1) firm size, (2) age, (3) the book-to-market, and (4) share turnover. Stocks are divided based on the sample median of each characteristic.

Table 3.6: Performance of hedge fund option strategies - subsample analyses.

This table reports the median returns of quarterly tracking portfolio of options based on aggregate hedge funds quarter-end option strategies using Chen et al. (2000) approach. The sample period is between 1999:Q1 and 2012:Q3. We classify stocks into four dimensions (size, age, book-to-market ratio, and share turnover) based on the median cutoff point in our sample. Following Aragon and Martin (2012) strategy classifications, for each quarter and manager's option holding position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; bear strategy if the manager reports a put option only; protective put strategy if the manager reports a put option with an existing equity position; and, straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. At the end of each quarter, we compute the aggregate hedge funds' option positions for each stock according to the strategy classifications. To illustrate, In Panel A, at the beginning of each month, we form a short-term ATM tracking portfolio of options based on last quarter-end bull strategies of all managers. This portfolio includes all call options whose maturity is between 45 and 90 days and absolute delta is between 0.4 and 0.6 at the beginning of that month. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the portfolio weights. We track the monthly raw returns of these weighted portfolios over the subsequent months. We report the median raw return. This procedure applies similarly to bear, protective put, and straddle strategies. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. A Wilcoxon two-sample test is used to test whether the returns between the two portfolios are significantly different from each other. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| **Panel A: Size** | | | | **Panel B: Age** | | | |
|---|---|---|---|---|---|---|---|
| **Strategy** | **Small** | **Large** | **Difference** | **Strategy** | **Young** | **Old** | **Difference** |
| Bull | -1.452*** | -1.228* | -0.224 | Bull | -0.933* | -1.355*** | 0.422 |
| | (12.413) | (6.06) | | | (8.074) | (5.288) | |
| Bear | -1.65*** | -1.319*** | -0.331*** | Bear | -1.577*** | -1.473*** | -0.104 |
| | (6.635) | (4.595) | | | (6.476) | (5.143) | |
| Protective Put | -2.301*** | -1.763*** | -0.538** | Protective Put | -1.908*** | -1.784*** | -0.124 |
| | (14.818) | (4.411) | | | (5.345) | (4.742) | |
| Straddle | -1.29*** | -0.885*** | -0.405*** | Straddle | -0.681*** | -0.884*** | 0.203 |
| | (4.668) | (1.771) | | | (2.265) | (1.894) | |

| **Panel C: Book-to-market** | | | | **Panel D: Share Turnover** | | | |
|---|---|---|---|---|---|---|---|
| **Strategy** | **Growth** | **Value** | **Difference** | **Strategy** | **Low** | **High** | **Difference** |
| Bull | -1.061* | -0.921** | -0.14 | Bull | -1.209*** | -1.101 | -0.108 |
| | (6.761) | (6.024) | | | (4.956) | (7.183) | |
| Bear | -1.54*** | -1.209*** | -0.331 | Bear | -1.761*** | -0.967*** | -0.794 |
| | (5.121) | (7.159) | | | (5.274) | (4.89) | |
| Protective Put | -1.974*** | -1.007*** | -0.967 | Protective Put | -1.648*** | -2.037*** | 0.389 |
| | (4.703) | (4.649) | | | (4.581) | (5.253) | |
| Straddle | -0.972*** | -0.986*** | 0.014 | Straddle | -0.776*** | -0.947*** | 0.171 |
| | (2.052) | (3.179) | | | (2.121) | (2.136) | |

The literature suggests that information asymmetry is greatest among small and young stocks. If hedge fund option positions are speculative in nature, we would expect greater outperformance among these stocks. Countering this prediction, however, we find that option strategies on small stocks generally fare the worst across all options trading strategies, ranging between $-0.538\%$ and $-0.224\%$ per month (see Table 3.6). These hedge fund option strategies are also equally likely to underperform between young versus old stocks and value versus growth stocks. Lastly, using share turnover as a proxy for stock uncertainty, as suggested by Barinov (2014), we still find no evidence of substantial performance differentiation between stocks with high and low uncertainties.

### 3.4.4 Robustness Test 3: Evidence From Future Earnings Announcements

Our next robustness test involves testing whether hedge fund option positions possess private information by examining their relations with firm's future earnings news. Since earnings announcements are often regarded as one of the most important corporate event for market participants, there is voluminous research that attempt to identify the group of investors who can exploit the event. The literature suggests that professional manager trading is positively associated with subsequent earnings announcements. Ali et al. (2004) document certain institutional managers do trade on information about future firm performance as evidenced by the positive association between changes in holdings and subsequent earnings announcement returns. Ke and Petroni (2004) investigate transient investors trading behavior before a break in a string of consecutive earnings increases. The authors find transient investors can predict the break at least one quarter in advance of the break quarter, consistent with transient institutions obtaining information regarding the impending break from private communications with management. Yan and Zhang (2009) and Baik et al. (2010) also arrive at similar conclusions on return predictability with transient investors and local investors, respectively.

We obtain quarterly earnings announcement dates from Compustat. We consider three different window periods to compute earnings announcement abnormal return: $[-5, 1]$, $[-3, 1]$, and $[-1, 1]$, with zero being the event date. Our inclusion of the next trading day is motivated by Berkman and Truong (2009), who show a significant portion of firms report their earnings after the close of the trading day. Thus, our choice of earnings announcement windows ensure that price changes due to the news dissemination is well-captured and reflected in our analyses. As in previous sections, we form a short-term ATM option portfolio at the beginning of each announcement windows based on disclosure of the last quarter-end hedge fund option strategies. We then compute the buy-and-hold returns achieved by the four option strategies over these windows.

Table 3.7: Performance of hedge fund option strategies - returns on future earnings announcements.

This table reports the median returns of quarterly tracking portfolio of options over different earnings announcement intervals based on hedge funds quarter-end option strategies disclosures using Chen et al. (2000) aggregation approach. The sample period is between 1999:Q1 and 2012:Q3. Following Aragon and Martin (2012) strategy classifications, for each quarter and manager's option holding position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; bear strategy if the manager reports a put option only; protective put strategy if the manager reports a put option with an existing equity position; and, straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. We report the median portfolio returns achieved in three different earnings announcement intervals: $[-1, 1]$, $[-3, 1]$, and $[-5, 1]$. For each earnings announcement interval, we form a short-term ATM tracking portfolio of options based on last quarter-end bull strategies of all managers. This portfolio includes all call options whose maturity is between 45 and 90 days and absolute delta is between 0.4 and 0.6 at the beginning of the event window. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the portfolio weights. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| **Strategy** | **[-1,1]** | **[-3,1]** | **[-5,1]** |
|---|---|---|---|
| Bull | 0.007 | 0.02 | 0.002 |
| | (0.308) | (0.21) | (0.266) |
| Bear | 0.002 | -0.021 | -0.015 |
| | (0.439) | (0.664) | (0.603) |
| Protective Put | -0.043*** | -0.063** | -0.066** |
| | (0.444) | (0.173) | (0.41) |
| Straddle | 0.014 | 0.004 | 0.009 |
| | (0.056) | (0.061) | (0.058) |

Table 3.7 reports the estimation results for our event study approach. Although the signs of some of the returns of tracking option portfolio are positive, they are not precisely estimated. Furthermore, taking the bull strategy as example, a return of 0.02% over a five-day interval translates into an annualized return of 1.01% ($0.02 * (252/5)$), which, as an economic magnitude, is deemed marginal. A protective put tracking option portfolio has the worst yield, earning median returns from $-0.07\%$ for a seven-day interval to $-0.043\%$ for a three-day interval.

### 3.4.5 Robustness Test 4: Comparison with Other Institutional Investors

To complete our analyses, we compare the option strategies' performance between hedge funds and other institutional investors. Griffin and Xu (2009) find that, over the whole 1986-2004 period, the difference in stock selection skills between hedge funds and mutual funds is 1.32% per year and is only marginally significant, leading the authors to raise serious questions about the perceived superior managerial ability of hedge funds. From Section 3.3, our 13F/Thomson Reuters data consists of $2,172$ non-hedge fund institutional managers. Of these, about 6% trade in the options market, a figure that is significantly lower than that for hedge funds (30%). Table 3.8 reports the differences in option strategies performance of these two groups of investors. Contrary to prediction, hedge funds generally underperform non-hedge funds across all strategy types but the differences are not statistically significant. Our results seem to resonate well with the conclusion made by Griffin and Xu (2009).

Table 3.8: Performance comparisons between hedge funds and other institutional investors.

This table reports the median returns of quarterly tracking portfolio of options on both hedge funds and other institutional investors quarter-end option strategies disclosures using Chen et al. (2000) aggregation approach. The sample period is between 1999:Q1 and 2012:Q3. Following Aragon and Martin (2012) strategy classifications, for each quarter and manager's option holding position, we classify the observed option position as bull strategy if the manager reports a call option with or without an existing equity position; bear strategy if the manager reports a put option only; protective put strategy if the manager reports a put option with an existing equity position; and, straddle if the manager reports both call and put options simultaneously, with or without an existing equity position. At the end of each quarter, we compute the aggregate hedge funds' option positions for each stock according to the strategy classifications. To illustrate, In Panel A, at the beginning of each month, we form a short-term ATM tracking portfolio of options based on last quarter-end bull strategies of all managers. This portfolio includes all call options whose maturity is between 45 and 90 days and absolute delta is between 0.4 and 0.6 at the beginning of that month. The reported market value of option holdings (i.e. the product of option prices and the number of option contracts) are used to construct the portfolio weights. We track the monthly raw returns of these weighted portfolios over the subsequent months. We report the median raw return. This example applies similarly to bear strategy, protective put strategy, and straddle strategy. We repeat this for other institutions as well. A one-sample nonparametric sign test is used to test whether the reported median returns are significantly differed from 0. A Wilcoxon two-sample test is used to test whether the returns between the two portfolios are significantly different from each other. Standard deviations of portfolio returns are reported in parentheses. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

| **Strategy** | **Hedge funds** | **Other institutional investors** | **Difference** |
|---|---|---|---|
| Bull | -1.411** | -0.935 | -0.476 |
| | (5.993) | (6.234) | |
| Bear | -1.241** | -1.642*** | 0.401 |
| | (4.312) | (4.276) | |
| Protective put | -1.588*** | -1.432*** | -0.156 |
| | (4.334) | (4.098) | |
| Straddles | -0.887*** | -0.874*** | -0.013 |
| | (1.693) | (1.884) | |

## 3.5 Conclusion

This paper reviews the literature on hedge fund performance targeting the usage of options by fund managers. Based on detailed investigations on their long option positions, we conclude there is little evidence that suggests hedge fund managers are skilled in executing informed trades in the options market. Hypothetical portfolios that mimic these hedge fund option strategies yield significant negative monthly returns across all strategies. Nonetheless, we note that one drawback of our study is we may not be able to generalize our conclusions to other hedge fund derivative positions such as futures, swaps, or even short option positions, which are not observable in our data. Thus, future research that has access to such information may prove fruitful.

# Chapter 4

# How Valuable Are Brokerage Relationships for Mutual Funds? Evidence From The Collapse of Lehman Brothers

## 4.1 Abstract

Using the sudden collapse of Lehman Brothers as a natural experiment, we examine whether mutual funds derive value from their institutional brokerage relationships. We find the impact of a damaged institutional brokerage relationship is greatest among mutual fund clients with concentrated brokerage networks and funds that specialize in small-cap stocks. Based on a DiD analysis, we find a drop in monthly fund alphas ranging from 34.2 and 70.9 basis points per month in risk-adjusted returns arising from a weakening brokerage relationship. Collectively, our results support the view that information and research services from the sell-side industry are indispensable inputs in enhancing mutual fund performance.

## 4.2 Introduction

How valuable are institutional brokerage relationships to mutual fund managers? The mutual fund industry pays billions of dollars in commissions each year to the sell-side industry in return for premium brokerage services (e.g., Goldstein et al. (2009), Greenwich Associates (2011)). The value of these services for brokerage clients such as mutual funds is documented to include superior trade execution (Anand et al. (2011), Cici et al. (2014)), profitable analyst recommendations (Green (2006), Irvine et al. (2007)), Xie (2014)), favorable IPO allocations (Reuter (2006), Goldstein et al. (2011)), access to management conferences (Green et al. (2014)), and liquidity support (Aitken et al. (1995)).[1]

Thus, the literature reports evidence suggesting that institutional brokerage services serve as valuable input to a fund's portfolio performance. However, the literature to date does not directly measure the overall incremental contribution of these services to mutual fund return performance. Recent empirical evidence shows problems that arise from brokerage relationships. For example, brokerage relations built around soft dollar payment arrangements may have (un)intended consequences of excessive churning by fund managers that could lead to detrimental effects on fund returns (Edelen et al. (2012, 2013)).[2] Further, soft dollar relations may result in a conflict of interest that hurts fund investors' returns if fund managers choose brokers based on their ancillary services rather than seeking providers who can best execute trades at the lowest costs. John Bogle (Bogle (2009), p. 52), founder of Vanguard, questions the value of these brokerage services, stating,

[1] The practice of bundling trade executions and research services is permitted under the safe harbor clause of Section 28(e) of the Securities and Exchange Act so long as the managers are acting in good faith that the commission payments are reasonable in relation to the value of the brokerage and research services provided (see, e.g., `https://www.sec.gov/rules/interp/34-23170.pdf`).

[2] For instance, Goldstein et al. (2011) find direct evidence on institutions engaging in churning stocks and paying abnormally large commissions to the lead underwriters of upcoming favorable IPOs.

*"... the constant updating of financial information by talented, often brilliant, security analysts and strategists clearly enhances market efficiency and lowers execution costs. But the failure of the analyst community to foresee the unhappy results of the flawed financial statements of Enron Corporation, WorldCom, and, more recently, scores of banks and investment banks hardly suggests a high-value-added research product."* (Bogle (2009) p. 52).

Consequently, there is no clear evidence on whether additional sell-side services in managerial investment decisions substantially outweigh the excess trading commissions paid. There is still much that we do not know about how fund managers' performance is related to their long-term relationships with their institutional brokers, primarily due to the inherent difficulty in capturing and measuring the value of this relationship capital. In this paper, we advocate a new empirical approach to tackle the issue by addressing a mirror question: What happens to the mutual fund's portfolio performance when brokerage relationships are disturbed or broken due to external factors? The answer to this question is central to understanding whether institutional brokers create value for their clients. Our main contribution to the fund–brokerage relationship literature is that we exploit the recent collapse of Lehman Brothers as a quasi-natural experimental setting that allows us to measure the value of mutual funds' relations with their institutional brokers.[3]

The demise of Lehman Brothers on September 15, 2008 marks the largest bankruptcy event in U.S. corporate history. Although its brokerage arm was initially excluded from the parent company's bankruptcy, the complexity of the intra-organizational dependency ultimately led to the unit's liquidation.[4] Within days, Barclays Capital

[3]The impact of Lehman's collapse on the financial market has been investigated extensively across many studies, such as those of Aragon and Strahan (2012), Fernando et al. (2012), May (2014), and Dumontaux and Pop (2013).

[4]The problems faced by the brokerage arm unit are precisely described in the Trustee Pre-

announced its intention to acquire Lehman's North American investment banking, trading, and brokerage divisions. Upon obtaining approval from the bankruptcy court, the majority of Lehman's former clients were transferred to Barclays on September 23, 2008. Figure 4.1 traces the brokerage relationships between Lehman Brothers and its mutual fund clients over time. Given the significant presence of Lehman in the U.S. brokerage landscape, it is not surprising to observe that over 60% of mutual funds employed Lehman Brothers as one of their top brokers prior to the bankruptcy. In the aftermath, a sizeable portion of Lehman's former mutual fund clients ended up with Barclays' brokerage services. Although Barclays also assimilated a significant number of former Lehman employees into its business, as many as one-third of these employees were immediately laid off, with another one-third leaving in the subsequent years.[5] This hastily drawn-up acquisition has been described as abrupt and chaotic.[6] More importantly, it constitutes an ideal platform for us to observe the disruption of valued brokerage relationships that mutual funds had with Lehman as a result of its drastic internal downsizing and restructuring.

The question of whether Lehman's collapse was followed by poor performance for its mutual fund clients goes to the heart of our motivation to test and measure the

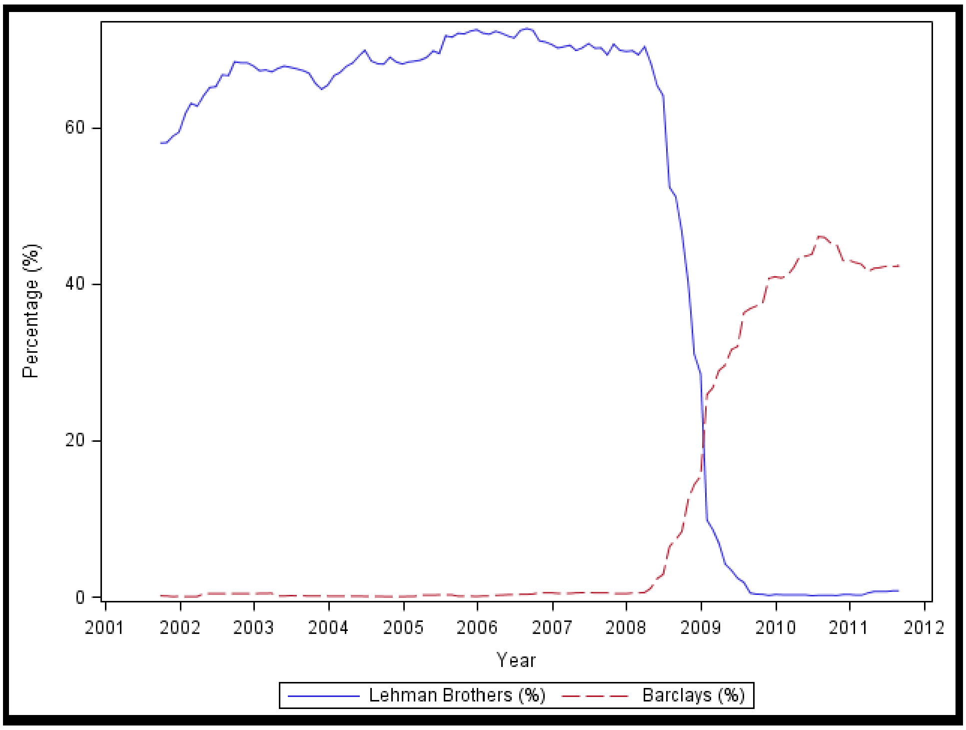
liminary Investigation Report: "*Tangible negative effects on [Lehman Brothers] from the crisis confidence... rendered [its brokerage unit] unable to obtain adequate financing on an unsecured or even secured basis, caused the departure of customers, and spurred an increase in failed transactions and additional demands for collateral by clearing banks and others.*" (Trustee Report, p. 26). For a more in-depth discussion on the Lehman Brothers' bankruptcy resolution process, see Fleming and Sarkar (2014), Wiggins et al. (2014), and Wiggins and Metrick (2014a,b)

[5]As part of the acquisition agreement, Barclays only retained approximately 9,000 former Lehman employees out of 25,000. Although Barclays also took on a potential liability of $2.5 billion to be paid as severance as part of the agreements, this only applied if it decided not to keep those Lehman employees beyond the guaranteed 90 days. Follow-up evidence suggests there were significant layoffs, with some 65% of Lehman's former employees initially taken on by Barclays leaving in the first two years (see http://www.cnbc.com/id/100453209 and http://www.ft.com/intl/cms/s/0/2c3436a8-a947-11dd-a19a-000077b07658.html\#axzz3jmi5gBJD,).

[6]As described by James Peck, the court bankruptcy judge who handled the Lehman case, "*I have to approve this transaction because it is the only available transaction... This is the most momentous bankruptcy hearing I've ever sat through. It can never be deemed precedent for future cases. It's hard for me to imagine a similar emergency.*" Available at http://news.bbc.co.uk/2/hi/business/7626624.stm.

Figure 4.1: The collapse of Lehman Brothers and its mutual fund clientele.

This figure presents the monthly percentage of U.S. mutual funds that employ Lehman Brothers as one of their top ten brokerage firms between September 2001 and August 2011. We obtain the information from Form N-SARs recorded in the SEC EDGAR database.

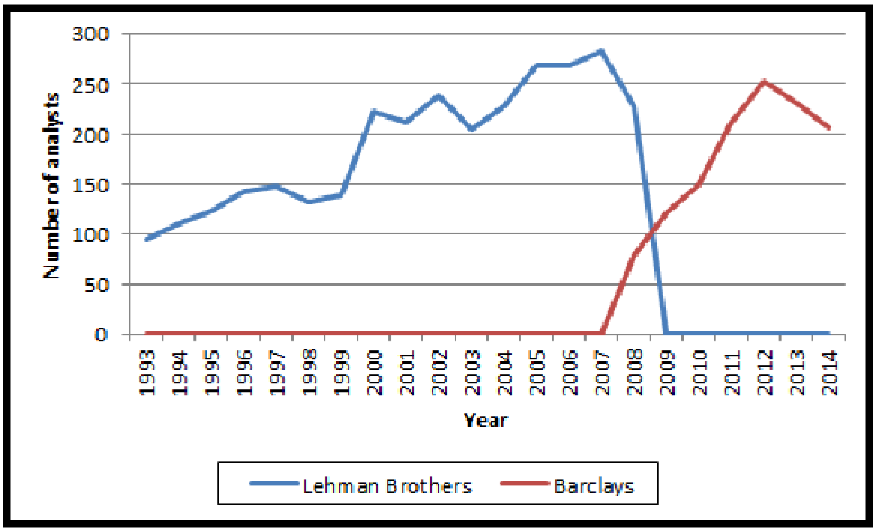



value of brokerage relationships. In a knowledge-intensive industry such as that of institutional brokerage houses, it is reasonable to entertain the notion that human capital may well be the most important input of the firm's production function. As Mailath and Postlewaite (1990) postulate, a firm is "*a network of people, each with an understanding about how information and goods move within the firm. They know whom to contact about particular problems that may arise and they know the strengths and weaknesses of their co-workers.*" Empirical studies of the institutional brokerage industry also lend support to this statement. For instance, some papers point out that the differential performance of individual analysts can be attributed to a number of factors, including the resources and support they receive from their brokerage firms (Clement (1999), Jacob et al. (1999)), the quality of colleagues (Groysberg and Lee (2008)), and social network connectivity (Horton and Serafeim

(2009)). The importance of these relationships is succinctly described by Josie Esquivel (see Groysberg and Healy (2013), p. 30), a former Lehman's star analyst, who once commented: "*How do you get things done in a service organization? You leverage your relationships, the relationships it took you years to build. They're based on trust, and trust is not easy to come by on Wall Street.*" Importantly, Figure 4.2 shows the number of analysts employed by both Lehman Brothers and Barclays over the years. Two striking features arise: (1) upon the 2008 collapse, approximately one-third of former Lehman analysts continue to stay with Barclays and (2) it took Barclays several years to rebuild the former Lehman brokerage research house.

Figure 4.2: The collapse of Lehman Brothers and its research analysts.

This figure presents the number of analysts employed by Lehman Brothers and Barclays over the years. We obtain the information from the Institutional Brokers Estimate System (IBES).




Motivated by these stylized facts, we hypothesize that the drastic change within Lehman's brokerage unit may have damaged its relationships with mutual fund clients, leading to the deterioration of fund performance in the aftermath.[7] More-

[7]The unexpected removal of Lehman's past employees by Barclays' downsizing decisions could have unintended negative consequences on client mutual funds' performance via at least two chan-

over, using a return decomposition approach of DGTW and Kacperczyk et al. (2008), we also examine the relative importance between the information channel (i.e. analyst recommendations) and transaction channel (i.e. execution costs) in explaining the observed performance deteriorations.

It is worth pointing out that there are several plausible counterfactuals that could bias against finding evidence in favor of our hypothesis. First, it is reasonable to expect that the handling of Lehman's brokerage unit by both the authorities and Barclays ensured little disruption for its mutual fund clients. For instance, while Barclays had retrenched many of Lehman's former executives, it probably kept many of its core, highly valued employees, thus minimizing the fallout for its significant client relationships. Second, due to major regulatory changes such as Regulation Fair Disclosure and the Global Research Analysts Settlement in the early 2000s, the value of institutional brokerage to mutual funds may have been significantly diminished anyway, for example through the loss of opportunities for the transfer of private information to mutual fund clients (see Kadan et al. (2009), Goldstein et al. (2009), Bhojraj et al. (2012)), reducing the chances of finding further fund performance deterioration following the Lehman collapse. Third, the negative effects of a rupture in brokerage relationships can also be countered by the existence of other brokerage firms to which mutual funds could transfer. For instance, mutual fund giants such as Fidelity are often engaged with multiple brokerage firms, allowing them to spread their trades and solicit multiple research inputs (see Table 4.6 in the Appendix for details). Fourth, buy-side institutional investors such as mutual funds often undertake some of their research in-house to reduce reliance on sell-side providers. Using proprietary information on in-house research produced in a large

nels, for example. First, the direct brokerage relationships between the departed employees and their client mutual funds were cut or became obsolete. Second, from the point of view of existing Lehman employees who continued with Barclays, the departure of former colleagues severed their working relationships, which could have weakened their service to mutual fund clients.

fund management company, Rebello and Wei (2014) find that buy-side analysts' recommendations have significant influence over portfolio managers' investment decisions. This effectively reduces the reliance on information input from sell-side analysts (see Cheng et al. (2006)). For these reasons, therefore, we may not expect to find the Lehman collapse followed by poor fund performance but, rather, for it to only affect certain categories of mutual fund clients.

In this study, we identify Lehman mutual fund clients using Form N-SAR, which mandates all mutual funds to disclose their brokerage connections to the U.S. SEC semi-annually. We use a standard DiD approach to compare the performance between 730 Lehman and 366 non-Lehman mutual fund clients over the 48-month period between September 2006 and August 2010. We find the causal impact of Lehman's collapse is centered on funds with concentrated brokerage networks and specialization in small-cap investments. Our results indicate that these funds extract significant value from their long-term relationships with brokers.

Our finding of a discernible impact from damaged brokerage relationships on client funds that have concentrated brokerage networks is consistent with the view that these funds are more likely to depend on sell-side research services. For example, using transactional-level information on institutional trades, Goldstein et al. (2009) find that portfolio managers, especially smaller players, strategically channel a large portion of their order flows to a few brokers to increase their total commission payments in return for premium brokerage services. Based on the DiD analysis, our estimation of the drop in subsequent raw returns for these Lehman client funds averages $-0.709\%$ per month (or $-8.51\%$ per year) during the post-Lehman collapse period. Using Carhart's four-factor model as the metric yields similar results: On average, these funds experience a drop of $-0.508\%$ per month in alphas during the first year immediately after the collapse. However, the losses arising from a disrupted brokerage relationship diminish gradually over a longer time horizon. In contrast, we do not observe significant performance deterioration associated with a weakening brokerage relationship among client mutual funds that have large brokerage networks. Xie (2014) shows mutual fund managers tend to earn better returns on stocks that are covered by multiple brokerage analysts than on stocks that are not. By the same token, we highlight the risks of mutual funds that rely heavily on research services from a single broker because their performance is more likely to be adversely affected should the relationship turn sour, since they have limited contact with other brokerage firms.

We also show the impact of Lehman's collapse has undesirable performance consequences on its small-cap mutual fund clients. The literature contends that the central function of sell-side industry in securities markets is the alleviation of information asymmetries, particularly for small stocks, which are hard to value in nature (see, e.g., Womack (1996), Jegadeesh et al. (2004), Demiroglu and Ryngaert (2010), Mola et al. (2013)). Despite the findings that buy-side research helps to reduce reliance on sell-side analysts' research input, the literature also emphasizes that the value of the sell-side industry tends to concentrate in stocks not followed by buy-side analysts or in funds with low overall buy-side coverage (see Rebello and Wei (2014), Frey and Herbst (2014)). Moreover, Groysberg et al. (2013) point out that buy-side analysts typically cover significantly more stocks than sell-side analysts, which could lead to reduced depth and value in their analyses of any given stock, especially among those with small market capitalization. Lacking information on buy-side brokerage research, we instead hypothesize a brokerage relationship perturbation could have a larger undesired effect on small-cap mutual funds than on others. Again, we find that, among small-cap mutual funds, those that received brokerage services from Lehman suffered significantly more in the aftermath: The disturbance of brokerage ties led to a drop in raw returns of $-0.342\%$ per month during the years following the Lehman collapse. The drop in performance, using either factor-based alphas or objective-adjusted returns, is both statistically and economically significant, ranging between $-0.203\%$ and $-0.495\%$ per month. This observation does not extend to funds with other investment objectives, such as a large-cap investment style. Taken together, we interpret the results as being consistent with the view that funds that specialize in hard-to-value securities are more likely to leverage their relationship with sell-side brokerage firms.

Lastly, we extend our baseline results by identifying the relevant channels that drive the observed performance effects. We identify two possible channels. The first channel is the information channel. For instance, Green (2006), Irvine et al. (2007), and Xie (2014) find that early access to stock recommendations provides brokerage firm clients with incremental investment value. The second channel is the liquidity or trade execution channel. Both Anand et al. (2011) and Cici et al. (2014) argue that the trade implementation process is economically important and can contribute to relative portfolio performance. Reuter (2006) also shows fund managers routinely receive favorable IPO allocations from lead underwriters with whom they have good business relationships. Following the return decomposition approach of DGTW and Kacperczyk et al. (2008), we find strong evidence in support of the information channel. On average, severance of brokerage relationships leads to a drop in fund managers' stock selectivity skills of 3.96% to 5.76% per year, consistent with the classical view that sell-side analysts help their clients make better investment choices (Maber et al. (2014)). Moreover, the estimated magnitudes are comparable to those of Xie (2014), who shows mutual fund managers earn 6.3% in excess returns per year on stocks covered by their brokers relative to uncovered stocks.

Apart from contributing to the unsettled debate on the value of brokerage services in mutual fund performance, our paper also joins the emerging literature that studies the role of institutional brokerage firms in affecting fund managers' returns and trading behavior. For instance, Brown et al. (2013) show mutual fund herding behavior is strongly influenced by sell-side analysts' recommendation changes. Chung and Kang (2014) document strong comovement in the returns of hedge funds sharing the same prime broker, attributing the results to hedge funds' access to common information from the brokers. Neither paper, however, seeks to address the incremental value of brokerage services to mutual fund returns.

The rest of the chapter is structured as follows. Section 4.3 describes the data on mutual funds and their brokerage network disclosure. Section 4.4 provides the empirical methodology and results. Section 4.5 concludes.

## 4.3 Data

We assemble the mutual fund sample from the CRSP MFDB. Following Kacperczyk et al. (2005), Kacpercyzk and Seru (2007), and Kacperczyk et al. (2008), we focus exclusively on actively managed domestic equity mutual funds. Because of their constant efforts to identify securities mispricing and their high portfolio turnover, it is reasonable to expect these actively managed funds to be the most likely to benefit from stable long-term relationships with institutional brokers. Following Elton et al. (2001), we drop funds from the sample whose assets under management are less than $5 million in total to avoid incubation bias (see Evans (2010)). Other variables from the MFDB include fund monthly raw returns, fund size (TNA under management), fund family size (TNA of a fund's family), fund age, fund flows, the turnover ratio, and the expense ratio. To eliminate the issue of multiple fund share classes, we aggregate all observations pertaining to different share classes into one observation, since they have the same portfolio composition.[8] We compute each fund monthly raw return by dividing the fund's yearly total expense ratio by 12 and adding it back to the reported net returns in the CRSP MFDB. We also compute four additional mutual fund performance metrics commonly used in the literature: (1) Jensen (1968) alpha, (2) Fama and French (1993) alpha, (3) Carhart (1997) alpha, and (4) Khorana (1996, 2001) objective-adjusted return. To obtain the monthly Carhart alpha, for each fund–month observation, we estimate the past 36 months of factor loadings using Carhart's four-factor model:

$$R_{i,t} = \alpha_i + \beta_{1,i} R_{M,t} + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} UMD_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly mutual fund raw return, $R_{M,t}$ is the return to the value-weighted CRSP market index, and $SMB_t$, $HML_t$, and $UMD_t$ are the returns to the small-minus-big (SMB), high-minus-low (HML), and up-minus-down (UMD) portfolios to control for size, book-to-market, and return momentum effects, respectively. This approach helps to isolate the impact of Lehman's collapse on client mutual funds by controlling for these market-wide systematic effects. Using the estimated factor loadings, we compute Carhart's alpha by subtracting the expected return implied by the estimated four-factor model from the fund's current-month raw return. Similar procedures apply in computing Jensen's alpha, which retains the market factor only, and Fama and French's alpha, which retains all but the momentum factor. As Khorana (1996, 2001), we compute the fund's monthly objective-adjusted return as the difference between the fund's return and the average return of other funds with the same non-missing investment objective.

Next, we obtain details on mutual fund brokerage networks from Form N-SAR

[8]In the CRSP database, mutual funds are reported at the share class level, such as A, B, C, or institutional. The primary reason behind multiple fund share classes for the same fund, which share identical portfolio compositions, is due to clientele. They offer investors with various structures in front-end loads, rear-end loads, and 12b-1 fees (see Nanda et al. (2009) for an in-depth discussion.)

provided in the SEC EDGAR database. Under the Investment Company Act of 1940, all registered investment companies (including mutual funds) are required to file Form N-SAR semi-annually and, among other things, disclose the top ten brokerage firms to which the funds paid the most commissions during the six-month reporting period. The recent literature highlights the role of the fund family in determining the performance of individual funds managed under its umbrella (e.g., Chen et al. (2004), Gaspar et al. (2006), Bhojraj et al. (2012)). Based upon the economies of scale argument, it is reasonable to expect individual mutual funds within a family to benefit from research products and services acquired by other fund members. Following Reuter (2006), we therefore define our fund–brokerage relationship at the fund family level. Lastly, we merge these brokerage networks data with our mutual fund sample and provide comprehensive details in the Appendix. Our sample consists of $1,096$ unique mutual funds associated with 162 fund families covering the 48 months from September 2006 to August 2010.

Table 4.1, Panel A, plots the yearly aggregate commissions paid by the mutual fund industry from 1993 to 2011. Institutional commission payments constitute a lucrative form of revenue for brokerage houses. The total commission paid increases from $3 billion in 1995 to $9.5 billion in 2007. However, these commission payments are far from uniformly distributed among brokerage firms. Take 2007, for instance: 46% of the aggregate payments goes to the top ten brokerage houses. It is also evident that the share of the top ten brokerage firms is increasing over the years, consistent with the industry consolidation trend of recent years. Panel B provides a snapshot of these top ten brokerage firms in 2007 together with their respective percentage share of total commissions. Goldman Sachs appears to be the number one brokerage firm, receiving 6.45% of total payments, followed by Merrill Lynch (6.07%) and Credit Suisse (5.94%). Prior to its bankruptcy, Lehman Brothers was ranked in fourth place, receiving 5.78% of the total commissions, which is economically significant on its own. These bulge bracket firms generally also have a large group of mutual fund clients.[9] For example, approximately 60% of all mutual fund families use Lehman Brothers as one of their top brokers. Although Deutsche Bank generally has a smaller mutual fund client network, it still forms business ties with one-third of the mutual fund families, further emphasizing the concentration of the industry.

Table 4.1: Industrial organization of the mutual fund brokerage industry.

Panel A presents the aggregate brokerage commission (in billions of dollars) paid by the mutual fund industry from 1993 to 2011. We also report the market share of the top ten brokerage firms that received the most commissions each year. Panel B provides a snapshot on the top ten brokerage firms that received the most commissions in 2007.

**Panel A: Aggregate brokerage commissions paid by mutual fund industry**

| **Year** | **Aggregate commissions** | **Commissions received by top 10 brokerage firm (%)** |
|---|---|---|
| 1993 | 0.36 | 22.57 |
| 1994 | 1.81 | 26.31 |
| 1995 | 2.95 | 30.63 |
| 1996 | 3.93 | 30.22 |
| 1997 | 4.71 | 28.44 |
| 1998 | 5.60 | 30.98 |
| 1999 | 7.67 | 41.94 |
| 2000 | 7.76 | 39.14 |
| 2001 | 9.04 | 43.45 |
| 2002 | 9.29 | 48.62 |
| 2003 | 8.50 | 45.43 |
| 2004 | 8.97 | 44.65 |
| 2005 | 8.78 | 46.11 |
| 2006 | 9.64 | 45.47 |
| 2007 | 9.58 | 49.60 |
| 2008 | 8.63 | 51.83 |
| 2009 | 8.59 | 49.99 |
| 2010 | 8.24 | 49.74 |
| 2011 | 8.64 | 51.80 |

**Panel B: Top 10 brokerage firms in 2007**

| **Brokerage firm** | **Commissions received as percentage of total (%)** | **Clients as percentage of all fund families (%)** |
|---|---|---|
| Goldman Sachs | 6.45 | 45.76 |
| Merrill Lynch | 6.07 | 54.24 |
| Credit Suisse | 5.94 | 48.95 |
| Lehman Brothers | 5.78 | 54.81 |
| Citigroup | 5.49 | 52.51 |
| UBS | 5.36 | 50.95 |
| Morgan Stanley | 5.07 | 47.06 |
| J.P. Morgan | 4.08 | 44.00 |
| Deutsche Bank | 2.70 | 32.86 |
| Bear Stearns | 2.66 | 50.05 |

[9]Throughout the paper, a bulge bracket firm is defined as the top ten largest brokerage firms as of 2007: Goldman Sachs, Merrill Lynch, Credit Suisse, Lehman Brothers, Citigroup, UBS, Morgan Stanley, J.P. Morgan, Deutsche Bank, and Bear Stearns (see Panel B of Table 4.1).

We report the summary statistics of our mutual fund sample in Table 4.2. The average mutual fund monthly return is 0.43% per month, with a standard deviation of 5.96%. Both factor model-based alphas and objective-adjusted returns are smaller, ranging between four and 18 basis points per month. A typical mutual fund has $1710.97 million under management, is 16.85 years old, and has a turnover ratio of 84.3% and an expense ratio of 1.18%. Mutual funds typically engage in multiple bulge bracket firms, with 5.14 top ten relationships at a time, on average. Less than 25% of the funds use fewer than two brokerage firms. Overall, our sample statistics are consistent with past studies (e.g., Xie (2014), Edelen et al. (2012)).

Table 4.2: Mutual fund summary statistics.

This table reports descriptive statistics of mutual funds used in this paper. The sample period spans between September 2006 and August 2010, with a total of $1,096$ actively managed domestic equity mutual funds. We compute each mutual fund's monthly raw return by dividing the fund's yearly total expense ratio by 12 and adding it back to the reported net returns in the CRSP MFDB. We compute mutual fund monthly Jensen-$\alpha$, Fama-French-$\alpha$, and Carhart-$\alpha$ using each fund's past 36-month raw returns. We compute a mutual fund's objective-adjusted return by subtracting the average benchmark portfolio of other funds' monthly raw return which share the same investment objective from the fund's monthly raw return. *TNA* represents the fund's month-end TNA, in million of dollars. *FTNA* is the fund family's month-end TNA, in millions of dollars. *FundAge* is the number of years the fund exists since inception. *FundFlows* measures the fund's monthly inflow and outflow of assets. *Expense* is the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. *FundTurnover* is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNA of the fund. *NBulgeBracket* is the number of buldge bracket brokerage firms the mutual fund employs. The buldge bracket brokerage firms are Merrill Lynch, Goldman Sachs, Morgan Stanley, J.P. Morgan, Bear Stearns, Citigroup, UBS, Credit Suisse, Deutsche Bank, and Lehman Brothers.

| | **Mean** | **Standard deviation** | **First quartile** | **Median** | **Third quartile** |
|---|---|---|---|---|---|
| Raw return (%) | 0.43 | 5.96 | -2.75 | 1.31 | 4.14 |
| Jensen-$\alpha$ (%) | 0.18 | 2.17 | -0.94 | 0.08 | 1.16 |
| Fama-French-$\alpha$ (%) | 0.09 | 1.98 | -0.85 | 0.07 | 1.02 |
| Carhart-$\alpha$ (%) | 0.06 | 1.97 | -0.85 | 0.04 | 0.95 |
| Objective-adjusted (%) | 0.04 | 2.94 | -0.89 | -0.02 | 0.88 |
| *TNA* (in millions) | 1710.97 | 3465.70 | 126.50 | 465.30 | 1475.90 |
| *FTNA* (in millions) | 149305.28 | 273833.96 | 8253.50 | 36262.40 | 94734.80 |
| *FundAge* (in years) | 16.85 | 13.22 | 8.17 | 13.33 | 21.25 |
| *FundFlows* (%) | -0.21 | 9.59 | -1.49 | -0.52 | 0.68 |
| *Turnover* (%) | 84.30 | 72.91 | 37.00 | 66.99 | 111.00 |
| *Expense* (%) | 1.18 | 0.40 | 0.93 | 1.16 | 1.40 |
| *NBulgeBracket* | 5.14 | 3.16 | 2.00 | 6.00 | 8.00 |

## 4.4 Empirical Results

### 4.4.1 The Impact of Lehman's Collapse on Client Mutual Funds with Concentrated Brokerage Networks

Next we turn to estimating value of the long-term relationship capital mutual funds had with their brokers. A challenging issue in using the Lehman collapse as an event study is the omitted-variable bias inherited in the empirical design. This is because both asset returns and betas are not likely to be in equilibrium when there is a systematic panic in the financial market.[10] We mitigate this concern of short-term distortions in the market in two ways. First, since the Lehman collapse is both unexpected and has a systematic impact across the whole capital market including the mutual fund industry, the use of DiD should alleviate the omitted-variable issues. Second, as a robustness check, we use an objective-based performance measurement in the DiD analysis. This approach does not need to estimate the betas as required by factor-based approach like Fama and French (1993) and Carhart (1997).

In particular, based on Figure 4.1, we take advantage of the fact that some mutual funds are clients of Lehman Brothers but not of others and estimate the causal impact of Lehman's collapse on these mutual funds' performance using a DiD methodology. Under the DiD methodology, funds that engaged in Lehman's brokerage services as of August 31, 2008 are designated as the treated group ($N = 730$) and funds that did not serve as the control group ($N = 366$). Our DiD regression is thus specified as follows:

$$RawReturn_{i,t} = \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post_{i,t} + \beta_3 Lehman_{i,t} * Post_{i,t} + \epsilon_{i,t}, \quad (4.1)$$

[10] We thank the referee for pointing this issue.

where the dependent variable $RawReturn_{i,t}$ is fund $i$'s raw return in month $t$; $Lehman_{i,t}$ is an indicator variable that takes the value of one if fund $i$ was connected to Lehman Brothers as of August 31, 2008 and zero otherwise; and $Post$ is an indicator variable that takes the value of one after September 15, 2008 and zero otherwise. We cluster standard errors at the fund level, allowing an unrestricted covariance structure over time within funds. Bertrand et al. (2004) show this approach works well when the number of clusters is reasonably large, as in our current context. Under the DiD approach, we are effectively exploiting both the time series and cross-sectional variation in the data because we are comparing the performance of treated funds before and after Lehman's collapse with the performance of control funds over the same time period. Thus, any time-invariant omitted-variables would be perfectly taken care of under this approach. Our coefficient of interest is $\beta_3$ in Equation (4.1), which is the return differential from being a Lehman mutual fund client in the pre-collapse period compared to the post-collapse period. It measures the causal impact of Lehman's collapse on its clients' return performance.

As shown in Table 4.2, 50% of mutual funds in our sample receive research services from at least six bulge bracket brokerage firms. Consequently, the majority of these Lehman client funds can instead seek brokerage support from their other brokers in the aftermath, hindering one from detecting any significant impact from the Lehman collapse. On the other hand, smaller fund players may not be similarly endowed. Constrained by size, they tend to route a significant portion of their trades to a few brokers to boost their client status with the brokerage house and receive premium brokerage services (see Goldstein et al. (2009)). Based on this reasoning, we hypothesize funds that rely exclusively on services from a few brokerage firms will fare worse should their relationship with one of their brokers be damaged. To test our conjecture, we split our fund sample into two: funds that have concentrated brokerage networks and funds that engaged in multiple brokerage firms. We classify a fund as having a concentrated brokerage network if it employs fewer than four bulge bracket brokerage firms; otherwise, the fund is said to have a large brokerage network.

Table 4.3: The impact of Lehman Brother's bankruptcy on mutual funds with small and large brokerage networks.

This table presents the estimation results from DiD regressions that analyze the impact of Lehman Brother's collapse on mutual fund performance. The sample period spans between September 2006 and August 2010, with a total of $1,096$ actively managed domestic equity mutual funds. Panel A and B present the estimation results for mutual funds with small and large brokerage networks, respectively. We define a fund to have a small brokerage network if it employs less than four bulge bracket brokerage firms; otherwise the fund is defined as having a large brokerage network. The bulge bracket brokerage firms are Merrill Lynch, Goldman Sachs, Morgan Stanley, J.P. Morgan, Bear Stearns, Citigroup, UBS, Credit Suisse, Deutsche Bank, and Lehman Brothers. Column (1) presents the estimation results for Equation (4.1):

$$RawReturn_{i,t} = \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post_{i,t} + \beta_3 Lehman_{i,t} * Post_{i,t} + \epsilon_{i,t},$$

where the dependent variable $RawReturn_{i,t}$ is the mutual fund's monthly raw return. $Lehman_{i,t}$ is an indicator variable which takes the value of 1 if fund $i$ uses Lehman Brothers as one of its top ten brokers as of August 31, 2008, 0 otherwise. $Post_{i,t}$ is an indicator variable which takes the value of 1 after September 15, 2008, 0 otherwise. Column (2) presents the estimation results for Equation (4.2):

$$\begin{aligned} RawReturn_{i,t} \quad &= \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post1_{i,t} + \beta_3 Lehman_{i,t} * Post1_{i,t} \\ &+ \beta_4 Post2_{i,t} + \beta_5 Lehman_{i,t} * Post2_{i,t} \\ &+ \beta_6 Post3_{i,t} + \beta_7 Lehman_{i,t} * Post3_{i,t} + \epsilon_{i,t}, \end{aligned}$$

where *Post1* takes the value of 1 in the first year after the Lehman's collapse and 0 otherwise. *Post2* and *Post3* take the value of 1 for the period between September 2009 and February 2010 (6-month period) and March 2010 and August 2010 (6-month period), respectively, and 0 otherwise. We also include the fund characteristics as control variables in the regression analysis. *TNA* represents the fund's month-end TNA, in millions of dollars. $FTNA$ is the fund family's month-end TNA, in millions of dollars. *FundAge* is the number of years the fund exists since inception. *FundFlows* measures the fund's monthly inflow and outflow of assets. *Expense* is the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. *FundTurnover* is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNA of the fund. We use the logarithmic of *TNA*, $FTNA$, and *FundAge*. All control variables are lagged by one month. Column (3) - (6) replace the dependent variable with the fund's monthly Jensen-$\alpha$, Fama-French-$\alpha$, Carhart-$\alpha$, and objective-adjusted return, respectively. We compute mutual fund monthly Jensen-$\alpha$, Fama-French-$\alpha$, and Carhart-$\alpha$ using each fund's past 36-month raw returns. We compute a mutual fund's objective-adjusted return by subtracting the average benchmark portfolio of other funds' monthly raw return which shares the same investment objective from the fund's monthly raw return. All standard errors are clustered at the fund-level and are shown in parentheses under the estimated coefficients. The number of mutual funds and $R-$squared are presented. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

- Continued on next page -

| Panel A: Small brokerage network | | | | | | |
|---|---|---|---|---|---|---|
| | Raw | | Jensen | Fama-French | Carhart | Objective-adjusted |
| *Constant* | 0.357*** | 0.327 | -0.200 | -0.214 | -0.344* | -0.209 |
| | (0.036) | (0.250) | (0.209) | (0.199) | (0.199) | (0.204) |
| *Lehman* | 0.167 | 0.133 | 0.170 | 0.243 | 0.153 | 0.167 |
| | (0.133) | (0.125) | (0.135) | (0.153) | (0.115) | (0.117) |
| *Post* | -0.337*** | | | | | |
| | (0.055) | | | | | |
| *Lehman*Post* | -0.709*** | | | | | |
| | (0.201) | | | | | |
| *Post1* | | -0.632*** | 0.426*** | 0.066 | 0.278*** | 0.302*** |
| | | (0.073) | (0.068) | (0.079) | (0.073) | (0.067) |
| *Lehman*Post1* | | -1.123*** | -0.912*** | -0.990*** | -0.508** | -0.988*** |
| | | (0.356) | (0.210) | (0.251) | (0.244) | (0.225) |
| *Post2* | | 2.818*** | -0.159*** | -0.257*** | -0.017 | 0.027 |
| | | (0.060) | (0.049) | (0.048) | (0.051) | (0.068) |
| *Lehman*Post2* | | -0.151 | -0.107 | -0.142 | -0.378* | -0.136 |
| | | (0.214) | (0.279) | (0.293) | (0.226) | (0.218) |
| *Post3* | | -0.695*** | 0.194*** | -0.036 | 0.140** | 0.112 |
| | | (0.063) | (0.064) | (0.067) | (0.065) | (0.068) |
| *Lehman*Post3* | | -0.355* | -0.311* | -0.365* | -0.308 | -0.295 |
| | | (0.182) | (0.179) | (0.211) | (0.189) | (0.210) |
| *LOGTNA* | | -0.080*** | -0.045** | -0.013 | -0.018 | -0.027 |
| | | (0.026) | (0.021) | (0.018) | (0.018) | (0.019) |
| *LOGFTNA* | | -0.028 | 0.027 | 0.021 | 0.024 | 0.003 |
| | | (0.022) | (0.018) | (0.017) | (0.017) | (0.017) |
| *LOGFundAge* | | 0.062 | 0.042 | 0.015 | 0.004 | -0.008 |
| | | (0.048) | (0.042) | (0.044) | (0.040) | (0.037) |
| *FundFlows* | | 0.014*** | -0.003* | -0.002 | -0.000 | -0.001 |
| | | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| *Turnover* | | 0.000 | 0.001 | 0.000 | 0.000 | -0.000 |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Expense* | | 0.095 | 0.142** | 0.185*** | 0.176*** | 0.198*** |
| | | (0.089) | (0.068) | (0.063) | (0.058) | (0.064) |
| Number of funds | 171 | 171 | 171 | 171 | 171 | 122 |
| R-squared | 0.001 | 0.029 | 0.009 | 0.005 | 0.004 | 0.007 |

- Continued on next page -

| Panel B: Large brokerage network | | | | | | |
|---|---|---|---|---|---|---|
| | Raw | | Jensen | Fama-French | Carhart | Objective-adjusted |
| *Constant* | 0.434*** | 0.491*** | -0.225** | -0.086 | -0.114 | -0.057 |
| | (0.028) | (0.121) | (0.100) | (0.084) | (0.082) | (0.115) |
| *Lehman* | -0.040 | 0.055 | -0.089** | -0.071* | -0.019 | -0.027 |
| | (0.033) | (0.038) | (0.036) | (0.036) | (0.031) | (0.040) |
| *Post* | -0.610*** | | | | | |
| | (0.045) | | | | | |
| *Lehman*Post* | 0.058 | | | | | |
| | (0.051) | | | | | |
| *Post1* | | -0.986*** | 0.109** | -0.127** | 0.208*** | -0.114* |
| | | (0.055) | (0.051) | (0.058) | (0.052) | (0.063) |
| *Lehman*Post1* | | 0.055 | 0.082 | 0.078 | 0.062 | 0.084 |
| | | (0.063) | (0.058) | (0.067) | (0.058) | (0.072) |
| *Post2* | | 2.542*** | -0.231*** | -0.322*** | -0.179*** | -0.047 |
| | | (0.039) | (0.033) | (0.036) | (0.034) | (0.047) |
| *Lehman*Post2* | | 0.069 | 0.079** | 0.089** | 0.051 | 0.060 |
| | | (0.046) | (0.039) | (0.042) | (0.040) | (0.055) |
| *Post3* | | -0.962*** | -0.085* | -0.235*** | -0.060 | -0.082 |
| | | (0.051) | (0.051) | (0.051) | (0.052) | (0.050) |
| *Lehman*Post3* | | 0.082 | 0.097* | 0.112* | 0.080 | 0.097* |
| | | (0.058) | (0.058) | (0.058) | (0.059) | (0.056) |
| *LOGTNA* | | -0.106*** | -0.044*** | -0.022*** | -0.026*** | -0.039*** |
| | | (0.011) | (0.008) | (0.007) | (0.007) | (0.010) |
| *LOGFTNA* | | -0.037*** | 0.032*** | 0.021*** | 0.009 | 0.017* |
| | | (0.009) | (0.008) | (0.007) | (0.006) | (0.009) |
| *LOGFundAge* | | 0.172*** | 0.089*** | 0.058*** | 0.058*** | 0.053*** |
| | | (0.022) | (0.017) | (0.014) | (0.014) | (0.018) |
| *FundFlows* | | 0.015*** | 0.001 | 0.001 | -0.001 | -0.000 |
| | | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Turnover* | | 0.001*** | 0.000** | 0.000 | 0.000* | -0.000** |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Expense* | | 0.098** | 0.139*** | 0.111*** | 0.073*** | 0.051 |
| | | (0.042) | (0.030) | (0.026) | (0.025) | (0.035) |
| Number of funds | 925 | 921 | 921 | 921 | 921 | 502 |
| R-squared | 0.002 | 0.031 | 0.004 | 0.003 | 0.005 | 0.001 |

Panel A of Table 4.3 shows the estimation results for funds with concentrated brokerage networks. Column (1) shows the estimation results for Equation (4.1). Before the collapse, the average return of a non-Lehman client fund is 0.357% per month, which is not significantly different from a Lehman client fund (the coefficient for *Lehman* is insignificant). As a whole, the mutual fund industry suffers significant performance deterioration in the two-year period following the collapse and is statistically significant at the 1% level. Pertaining to our hypothesis, we find substantial differences in performance between Lehman and non-Lehman client funds both before and after the collapse, since the estimated coefficients for *Lehman*Post* appear to be highly significant. The collapse of Lehman Brothers had a sizeable impact on funds that were highly dependent on the institutional broker: On average, these funds lost 0.709% per month during the two years in the aftermath because of the impediment in brokerage exchange.

In Column (2) of Panel A of Table 4.3, we relax the implicit assumption behind Equation (4.1), which assumes the impact of Lehman's collapse on fund performance is the same every year. To allow for a time varying effect, we construct three separate timing indicator variables: *Post1*, *Post2*, and *Post3*. Specifically, *Post1* takes the value of one in the first year after Lehman's collapse and zero otherwise. The variables *Post2* and *Post3* take the value of one for the six-month periods between September 2009 and February 2010 and between March 2010 and August 2010, respectively, and zero otherwise. Upon replacing these timing indicators with *Post* in Equation (4.1), we obtain

$$\begin{aligned} RawReturn_{i,t} &= \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post1_{i,t} + \beta_3 Lehman_{i,t} * Post1_{i,t} \\ &+ \beta_4 Post2_{i,t} + \beta_5 Lehman_{i,t} * Post2_{i,t} \\ &+ \beta_6 Post3_{i,t} + \beta_7 Lehman_{i,t} * Post3_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{4.2}$$

Under this specification, our coefficients of interest are $\beta_3$, $\beta_5$, and $\beta_7$. Now, by way of illustration, $\beta_3$ captures the impact of Lehman's collapse on its mutual fund clients during the first year immediately after the collapse (September 2008 to August 2009). A similar interpretation applies to $\beta_5$ and $\beta_7$. To control for any systematic differences in our sample, Column (3) of Panel A of Table 4.3 includes a host of other mutual fund variables, such as fund size, fund family size, fund age, fund flows, the turnover ratio, and the expense ratio. We use the logarithmic transformation of fund size, fund family size, and fund age. We lag the variables to partially mitigate the endogeneity issue. Consistent with our hypothesis, the adverse impact of Lehman's collapse on its mutual fund clients is greatest during the first year: These clients lost 1.123% per month during the first year in the aftermath. Nonetheless, such adverse impacts decayed over the years and are negligible beyond the first year (*Lehman*Post2* is insignificant and *Lehman*Post3* is marginally significant at the 10% level).

We also replace our dependent variable with either the fund's alpha (obtained from the factor models) or fund's objective-adjusted return. Replacing the fund's monthly raw returns with the Jensen's one-factor-alpha, we continue to find significant impact of Lehman's collapse on its mutual fund clients who have few other brokerage firms to rely upon. The estimated impact stands at −0.912% per month during the one year period immediately after September 2008. The results using the Fama-French three-factor-alpha and Carhart's four-factor-alpha are comparable, where *Lehman*Post1* is estimated to be −0.99 and −0.508, respectively. When we use the objective-adjusted return as the performance metric, the estimated impact is even larger: these mutual funds experience a significant deterioration in performance by −0.988% per month. Panel B of Table 4.3 repeats the analyses for funds with large brokerage networks. Across all specifications, the variables *Lehman*Post*, *Lehman*Post1*, *Lehman*Post2*, and *Lehman*Post3* appear to be either insignificant or marginally significant at the 10% level. There is also little noticeable impact of Lehman's collapse on funds that engage in multiple bulge bracket brokerage firms because the magnitude of these coefficients are generally less than 0.1% per month. Taken together, our results confirm the view that smaller fund players are significantly more dependent on the relationship with their brokers and losing such a relationship is detrimental to their performance.

Our results on the control variables can be summarized as follows. Consistent with Chen et al. (2004) and Yan (2008), we find that the logarithm of TNA ($LOGTNA$) is negatively related to fund performance. This indicates that large fund size is generally associated with inferior performance due to liquidity issues. In general, older funds or funds that are associated with a larger family complex are positively correlated with fund adjusted returns. This finding is in line with previous literature that argues there are economies of scales for trading commissions and research support for each individual fund (see Chen et al. (2004), Gaspar et al. (2006)). Lastly, funds that charge a higher expense ratio generally have better performance measures.

### 4.4.2 The Impact of Lehman's Collapse on Client Mutual Funds with Small-Cap Investment Objective

Next, in addition to sell-side research input, it is also common for buy-side managers such as mutual funds to seek internal advice from their own in-house research division. For instance, Cheng et al. (2006), using a large sample of U.S. equity funds for the period 2000–2002, document fund managers place an average weight of over 70% on buy-side analysts' research, 25% on sell-side analysts' research, and the remaining on independent research. It is, therefore, reasonable to expect the availability of buy-side research to reduce managers' reliance on sell-side input. However, both Groysberg et al. (2013) and Rebello and Wei (2014) point out the value of sell-side research revolves around stocks that are small and hard to value. In contrast to buy-side analysts who cover a large number of stocks, sell-side analysts are highly specialized, which allows them to produce research insights of greater value. Following these arguments, we conjecture that the collapse of Lehman should have had a larger impact on small-cap mutual funds than on others.

Table 4.4: The impact of Lehman Brother's bankruptcy on mutual funds with small-cap and non-small cap investment objective.

This table presents the estimation results from DiD regressions that analyze the impact of Lehman Brother's collapse on various mutual fund performances. The sample period spans between September 2006 and August 2010, with a total of $1,096$ actively managed domestic equity mutual funds. Panel A and B present the estimation results for mutual funds with small-cap and non-small-cap investment objective, respectively. We define a fund specializes in small-cap securities if its Lipper classification code is one with either "SCCE", "SCGE", or "SCVE", its Strategic Insight Objective code is "SCG", or its Wiesenberger Objective Code is "SCG". Column (1) presents the estimation results for Equation (4.1):

$$RawReturn_{i,t} = \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post_{i,t} + \beta_3 Lehman_{i,t} * Post_{i,t} + \epsilon_{i,t},$$

where the dependent variable $RawReturn_{i,t}$ is the mutual fund's monthly raw return. $Lehman_{i,t}$ is an indicator variable which takes the value of 1 if fund $i$ uses Lehman Brothers as one of its top ten brokers as of August 31, 2008, 0 otherwise. $Post_{i,t}$ is an indicator variable which takes the value of 1 after September 15, 2008, 0 otherwise. Column (2) presents the estimation results for Equation (4.2):

$$\begin{aligned} RawReturn_{i,t} \quad &= \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post1_{i,t} + \beta_3 Lehman_{i,t} * Post1_{i,t} \\ &+ \beta_4 Post2_{i,t} + \beta_5 Lehman_{i,t} * Post2_{i,t} \\ &+ \beta_6 Post3_{i,t} + \beta_7 Lehman_{i,t} * Post3_{i,t} + \epsilon_{i,t}, \end{aligned}$$

where *Post1* takes the value of 1 in the first year after the Lehman's collapse and 0 otherwise. *Post2* and *Post3* take the value of 1 for the period between September 2009 and February 2010 (6-month period) and March 2010 and August 2010 (6-month period), respectively, and 0 otherwise. We also include the fund characteristics as control variables in the regression analysis. $TNA$ represents the fund's month-end TNA, in millions of dollars. $FTNA$ is the fund family's month-end TNA, in millions of dollars. *FundAge* is the number of years the fund exists since inception. *FundFlows* measures the fund's monthly inflow and outflow of assets. *Expense* is the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. *FundTurnover* is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNA of the fund. We use the logarithmic of $TNA$, $FTNA$, and *FundAge*. All control variables are lagged by one month. Column (3) - (6) replace the dependent variable with the fund's monthly Jensen-$\alpha$, Fama-French-$\alpha$, Carhart-$\alpha$, and objective-adjusted return, respectively. We compute mutual fund monthly Jensen-$\alpha$, Fama-French-$\alpha$, and Carhart-$\alpha$ using each fund's past 36-month raw returns. We compute a mutual fund's objective-adjusted return by subtracting the average benchmark portfolio of other funds' monthly raw return which shares the same investment objective from the fund's monthly raw return. All standard errors are clustered at the fund-level and are shown in parentheses under the estimated coefficients. The number of mutual funds and $R-$squared are presented. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

- Continued on next page -

| Panel A: Small-cap fund | | | | | | |
|---|---|---|---|---|---|---|
| | Raw | | Jensen | Fama-French | Carhart | Objective-adjusted |
| *Constant* | 0.375*** | 0.609** | -0.170 | -0.020 | -0.037 | -0.071 |
| | (0.044) | (0.287) | (0.223) | (0.201) | (0.181) | (0.203) |
| *Lehman* | 0.120* | 0.261*** | 0.082 | 0.139* | 0.082 | 0.118 |
| | (0.067) | (0.092) | (0.079) | (0.076) | (0.065) | (0.077) |
| *Post* | -0.286*** | | | | | |
| | (0.062) | | | | | |
| *Lehman*Post* | -0.342*** | | | | | |
| | (0.098) | | | | | |
| *Post1* | | -0.540*** | 0.584*** | 0.103 | 0.355*** | 0.175** |
| | | (0.085) | (0.083) | (0.085) | (0.086) | (0.075) |
| *Lehman*Post1* | | -0.523*** | -0.404*** | -0.495*** | -0.203* | -0.450*** |
| | | (0.126) | (0.125) | (0.135) | (0.114) | (0.122) |
| *Post2* | | 2.982*** | -0.160** | -0.297*** | -0.116* | -0.005 |
| | | (0.075) | (0.067) | (0.062) | (0.062) | (0.072) |
| *Lehman*Post2* | | -0.049 | 0.107 | 0.030 | -0.051 | 0.033 |
| | | (0.100) | (0.094) | (0.092) | (0.089) | (0.099) |
| *Post3* | | -0.697*** | 0.264*** | -0.062 | 0.080 | 0.016 |
| | | (0.066) | (0.069) | (0.073) | (0.064) | (0.065) |
| *Lehman*Post3* | | -0.146 | -0.121 | -0.131 | -0.085 | -0.105 |
| | | (0.093) | (0.098) | (0.105) | (0.094) | (0.093) |
| *LOGTNA* | | -0.114*** | -0.035 | 0.016 | -0.002 | -0.029 |
| | | (0.029) | (0.021) | (0.019) | (0.017) | (0.019) |
| *LOGFTNA* | | -0.038* | 0.009 | -0.012 | -0.016 | -0.009 |
| | | (0.021) | (0.018) | (0.015) | (0.014) | (0.017) |
| *LOGFundAge* | | 0.179*** | 0.113** | 0.027 | 0.036 | 0.082* |
| | | (0.057) | (0.051) | (0.044) | (0.039) | (0.042) |
| *FundFlows* | | 0.019*** | 0.000 | 0.001* | 0.002** | 0.002** |
| | | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Turnover* | | 0.000 | 0.000 | -0.000 | -0.000 | -0.000 |
| | | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Expense* | | -0.063 | 0.091 | 0.136** | 0.118** | 0.083 |
| | | (0.091) | (0.071) | (0.063) | (0.059) | (0.066) |
| Number of funds | 162 | 162 | 162 | 162 | 162 | 162 |
| R-squared | 0.001 | 0.031 | 0.008 | 0.007 | 0.006 | 0.004 |

- Continued on next page -

| Panel B: Non-small-cap fund | | | | | | |
|---|---|---|---|---|---|---|
| | Raw | | Jensen | Fama-French | Carhart | Objective-adjusted |
| *Constant* | 0.409*** | 0.241** | -0.259*** | -0.154** | -0.237*** | -0.176* |
| | (0.026) | (0.113) | (0.091) | (0.078) | (0.079) | (0.106) |
| *Lehman* | -0.023 | 0.091** | -0.063* | -0.061* | -0.002 | 0.012 |
| | (0.031) | (0.037) | (0.034) | (0.035) | (0.031) | (0.041) |
| *Post* | -0.558*** | | | | | |
| | (0.042) | | | | | |
| *Lehman*Post* | 0.007 | | | | | |
| | (0.049) | | | | | |
| *Post1* | | -0.940*** | 0.138*** | -0.092 | 0.197*** | 0.030 |
| | | (0.051) | (0.047) | (0.056) | (0.050) | (0.062) |
| *Lehman*Post1* | | 0.021 | 0.042 | 0.068 | 0.082 | -0.027 |
| | | (0.060) | (0.055) | (0.066) | (0.057) | (0.072) |
| *Post2* | | 2.556*** | -0.204*** | -0.287*** | -0.103*** | -0.012 |
| | | (0.037) | (0.030) | (0.033) | (0.034) | (0.048) |
| *Lehman*Post2* | | 0.024 | 0.036 | 0.053 | -0.024 | 0.013 |
| | | (0.045) | (0.037) | (0.040) | (0.040) | (0.057) |
| *Post3* | | -0.908*** | -0.040 | -0.178*** | 0.009 | 0.001 |
| | | (0.048) | (0.049) | (0.049) | (0.050) | (0.057) |
| *Lehman*Post3* | | 0.029 | 0.034 | 0.058 | 0.013 | 0.028 |
| | | (0.057) | (0.056) | (0.057) | (0.058) | (0.063) |
| *LOGTNA* | | -0.099*** | -0.046*** | -0.025*** | -0.027*** | -0.037*** |
| | | (0.010) | (0.008) | (0.007) | (0.007) | (0.010) |
| *LOGFTNA* | | -0.018** | 0.034*** | 0.026*** | 0.019*** | 0.021*** |
| | | (0.008) | (0.007) | (0.006) | (0.006) | (0.008) |
| *LOGFundAge* | | 0.142*** | 0.078*** | 0.056*** | 0.051*** | 0.032* |
| | | (0.021) | (0.017) | (0.014) | (0.014) | (0.017) |
| *FundFlows* | | 0.011*** | -0.002 | -0.001 | -0.002** | -0.003 |
| | | (0.003) | (0.002) | (0.001) | (0.001) | (0.002) |
| *Turnover* | | 0.001*** | 0.000*** | 0.000 | 0.000** | -0.000 |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Expense* | | 0.112*** | 0.145*** | 0.124*** | 0.086*** | 0.102*** |
| | | (0.042) | (0.031) | (0.027) | (0.026) | (0.035) |
| Number of funds | 934 | 930 | 930 | 930 | 930 | 462 |
| R-squared | 0.002 | 0.030 | 0.004 | 0.003 | 0.005 | 0.002 |

Panels A and B of Table 4.4 examine funds that specialized in small-cap securities and those that did not, respectively. We classify a fund as specializing in small-cap securities if its Lipper classification code is either SCCE, SCGE, or SCVE; its Strategic Insight Objective code is SCG; or its Wiesenberger Objective Code is SCG. It is evident that Lehman's collapse significantly affected the performance of small-cap mutual funds. The coefficient estimate for *Lehman*Post* in Column (1) of Panel A shows the deterioration in monthly returns due to the Lehman collapse was about $-0.342\%$ per month. Using Equation (4.2), we find these adverse impacts are mainly concentrated in the first year but become negligible beyond that. Using other performance metrics, such as a fund's alpha and objective-adjusted returns, we also show small-cap funds generally lost between 20.3 and 49.5 basis points per month. Taken together, we show that our results are not driven by particular performance measurements. Consistent with the prediction that sell-side brokerage firms play an important role in alleviating the presence of information asymmetry in small-cap stocks, we observe no similar effects for non–small-cap mutual funds.

### 4.4.3 The Channel for Lehman's Bankruptcy Impact on Mutual Fund Performance

Our analyses at this stage reveal that a long-term brokerage relationship is valuable for buy-side managers. We have not, however, considered the possible channels that give rise to the observed performance effect. On one hand, the literature suggests that both analysts' recommendations and investor conferences can add value to the overall buy-side manager's profitability (e.g., Green (2006), Irvine et al. (2007), Xie (2014), Green et al. (2014)). On the other hand, brokerage houses can help managers to devise efficient trade executions, effectively lowering their transaction costs (e.g., Anand et al. (2011), Cici et al. (2014), Aitken et al. (1995)). Further, Reuter (2006) documents fund managers who have good business relationships with brokerage houses that serve as lead underwriters tend to be rewarded with favorable IPO allocations. To shed further insight on these issues, we turn to the recent mutual fund performance literature and decompose a fund's monthly raw returns as follows:

$$RawReturn = \underbrace{DGTW_{AS} + DGTW_{CS} + DGTW_{CT}}_{PortfolioReturn} + ReturnGap,$$

where $DGTW_{AS}$, $DGTW_{CS}$, and $DGTW_{CT}$ are the fund's average style, characteristic selectivity, and characteristic timing measures, respectively, proposed by DGTW; $DGTW_{AS}$ measures the returns earned by a fund due to its tendency to hold stocks with certain characteristics; and $DGTW_{CS}$ and $DGTW_{CT}$ measure the fund's overall stock selection and timing abilities, respectively. The sum of these three components equals the fund' hypothetical buy-and-hold portfolio return. As pointed out by DGTW, this decomposition provides a more accurate way to determine how funds generate returns. Lastly, *ReturnGap* measures the difference between the actual fund's returns and holdings returns. Kacperczyk et al. (2008) show *ReturnGap* captures funds' unobserved actions, including hidden benefits (e.g., interim trades and IPO allocations) and hidden costs (trading costs and commissions).

Table 4.5: The channel of the Lehman Brother's bankruptcy impact on mutual funds.

This table presents the estimation results from DiD regressions that analyze the channel of the Lehman Brother's bankruptcy impact on mutual fund performance. The sample period spans between September 2006 and August 2010, with a total of $1,096$ actively managed domestic equity mutual funds. We focus on mutual funds with small brokerage networks and funds that specialize in small-cap stocks. We define a fund to have a small brokerage network if it employs less than four bulge bracket brokerage firms; otherwise the fund is defined as having a large brokerage network. The bulge bracket brokerage firms are Merrill Lynch, Goldman Sachs, Morgan Stanley, J.P. Morgan, Bear Stearns, Citigroup, UBS, Credit Suisse, Deutsche Bank, and Lehman Brothers. We define a fund specializes in small-cap securities if its Lipper classification code is one with either "SCCE", "SCGE", or "SCVE", its Strategic Insight Objective code is "SCG", or its Wiesenberger Objective Code is "SCG". We present the estimation results for Equation (4.2):

$$\begin{aligned} DGTW_{CS,i,t} &= \beta_0 + \beta_1 Lehman_{i,t} + \beta_2 Post1_{i,t} + \beta_3 Lehman_{i,t} * Post1_{i,t} \\ &+ \beta_4 Post2_{i,t} + \beta_5 Lehman_{i,t} * Post2_{i,t} \\ &+ \beta_6 Post3_{i,t} + \beta_7 Lehman_{i,t} * Post3_{i,t} + \epsilon_{i,t}, \end{aligned}$$

where the dependent variable $DGTW_{CS,i,t}$ measures the fund's characteristics selectivity skills as proposed in DGTW. *Post1* takes the value of 1 in the first year after the Lehman's collapse and 0 otherwise. *Post2* and *Post3* take the value of 1 for the period between September 2009 and February 2010 (6-month period) and March 2010 and August 2010 (6-month period), respectively, and 0 otherwise. We also include the fund characteristics as control variables in the regression analysis. *TNA* represents the fund's month-end TNA, in millions of dollars. *FTNA* is the fund family's month-end TNA, in millions of dollars. *FundAge* is the number of years the fund exists since inception. *FundFlows* measures the fund's monthly inflow and outflow of assets. *Expense* is the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. *FundTurnover* is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month TNA of the fund. We use the logarithmic of *TNA*, *FTNA*, and *FundAge*. All control variables are lagged by one month. We also replace $DGTW_{CS,i,t}$ with $DGTW_{CT,i,t}$ and $ReturnGap_{i,t}$, respectively. $DGTW_{CT,i,t}$ measures the fund's characteristics timing skills and $ReturnGap_{i,t}$ is the difference between the fund's actual monthly return and buy-and-hold portfolio return as in Kacperczyk et al. (2008). All standard errors are clustered at the fund-level and are shown in parentheses under the estimated coefficients. The number of mutual funds and $R-$squared are presented. The superscripts $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

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| | Small brokerage network | | | Small-cap funds | | |
|---|---|---|---|---|---|---|
| | **DGTW CS measure** | **DGTW CT measure** | **Return Gap** | **DGTW CS measure** | **DGTW CT measure** | **Return Gap** |
| *Constant* | -0.674*** | -0.036 | 0.779*** | 0.494* | -0.193 | -0.493* |
| | (0.232) | (0.183) | (0.242) | (0.266) | (0.141) | (0.290) |
| *Lehman* | 0.028 | 0.048 | 0.059 | -0.021 | 0.051* | 0.085 |
| | (0.198) | (0.060) | (0.153) | (0.089) | (0.030) | (0.074) |
| *Post1* | 0.364*** | -0.234*** | -0.241*** | 0.453*** | -0.249*** | -0.296*** |
| | (0.072) | (0.050) | (0.055) | (0.086) | (0.060) | (0.069) |
| *Lehman*Post1* | -0.480** | -0.183 | -0.165 | -0.330*** | 0.084 | 0.020 |
| | (0.215) | (0.249) | (0.109) | (0.116) | (0.075) | (0.085) |
| *Post2* | 0.036 | 0.846*** | -0.032 | -0.043 | 0.915*** | 0.108* |
| | (0.049) | (0.052) | (0.053) | (0.070) | (0.062) | (0.063) |
| *Lehman*Post2* | 0.042 | -0.065 | -0.190 | 0.022 | -0.032 | 0.008 |
| | (0.213) | (0.172) | (0.158) | (0.094) | (0.090) | (0.078) |
| *Post3* | -0.145** | -0.134*** | 0.082 | -0.216*** | -0.168*** | 0.092 |
| | (0.065) | (0.033) | (0.053) | (0.073) | (0.032) | (0.066) |
| *Lehman*Post3* | 0.172 | -0.035 | -0.492*** | -0.013 | -0.063 | -0.055 |
| | (0.257) | (0.070) | (0.176) | (0.094) | (0.046) | (0.081) |
| *LOGTNA* | -0.007 | -0.002 | -0.005 | -0.042 | -0.020 | 0.040 |
| | (0.025) | (0.016) | (0.026) | (0.029) | (0.013) | (0.027) |
| *LOGFTNA* | 0.053** | -0.021* | -0.067*** | -0.020 | -0.002 | 0.002 |
| | (0.021) | (0.012) | (0.019) | (0.024) | (0.010) | (0.020) |
| *LOGFundAge* | 0.097** | 0.021 | -0.085* | 0.072 | 0.079* | -0.023 |
| | (0.043) | (0.036) | (0.047) | (0.058) | (0.041) | (0.061) |
| *FundFlows* | -0.002 | 0.003*** | 0.001 | 0.002** | 0.004*** | 0.001 |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Turnover* | -0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| *Expense* | 0.299*** | 0.069 | -0.209** | 0.141 | 0.053 | -0.042 |
| | (0.090) | (0.047) | (0.095) | (0.104) | (0.034) | (0.106) |
| Number of funds | 167 | 167 | 167 | 162 | 162 | 162 |
| R-squared | 0.011 | 0.025 | 0.011 | 0.017 | 0.034 | 0.013 |

Table 4.5 presents the estimation results for Equation (4.2) by replacing the dependent variable with either $DGTW_{CS}$, $DGTW_{CT}$, or *ReturnGap*. We observe that Lehman mutual fund clients with concentrated brokerage networks experienced significant deterioration in their overall stock selectivity skills after the collapse. Economically, the severance of the brokerage relationship translates into a decrease of 48 basis points per month in fund manager stock selection ability. This finding supports the view that sell-side analysts add value to their clients by helping them make better investment decisions. Our interpretation is consistent with that of Xie (2014), who shows stocks covered by a fund's brokers outperform uncovered stocks by 6.3% per year, on average. On the other hand, a damaged brokerage relationship does not have a major impact on managers' stock timing skills. We also show the adverse impacts of the collapse extended to managers' unobserved actions in the longer time period, since the coefficient estimate for *Lehman*Post3* is both statistically and economically significant. Similarly observations can be made when we look at small-cap mutual funds. Consistent with our earlier argument, we show these small-cap funds, which operate in a highly opaque investment environment, experienced a significant drop in their stock selectivity performance. The drop in the monthly $DGTW_{CS}$ measure arising from a weakening brokerage relationship amounts to 33 basis points per month. Based on these results, we contend that a loss of information advantage in the investment environment gives rise to the observed performance effects.

## 4.5 Conclusion

This paper exploits a natural experimental strategy to evaluate the value of brokerage relationships by studying the Lehman Brothers' bankruptcy event and its impact on the institutional broker's mutual fund clients. While previous studies on the fund–brokerage relationship are persuasive, it is possible that unobservable factors partially drive the results. Complementing past studies, we offer an alternative estimation technique to quantify these brokerage values. Our findings suggest that exogenous damage to a relationship with an important brokerage partner has a significant impact on funds that rely heavily on fewer brokers and that specialize in small-cap investing. Overall, our results suggest there is value in establishing stable long-term brokerage relationships with the sell-side industry, for it is an important determinant of mutual fund performance.

Owing to data limitations, our present investigation focuses solely on U.S. actively managed equity funds. Subsequent studies can extend our analyses by considering the fixed-income mutual funds segment. Unlike equity trading, most fixed-income securities are traded in the over-the-counter market and hence require dealers to execute principal transactions on their own accounts. Dealers are compensated by imposing a mark-up or mark-down spread on the transacted prices. In this setting, the dealer–client relationship basically involves reputation establishment and repeated interactions. From the client's perspective, the dealer's reputation is contingent on his or her willingness to quote a reasonable bid–ask spread, whereas, from the dealer's perspective, a client's reputation is based on his or her frequent acceptance of the dealer's terms of trade. Thus, the issue of the fund–brokerage relationship is especially important in the fixed-income market. We leave this extension to future work.

## 4.6 Appendix: Form N-SARs

This appendix has two objectives: 1) to illustrate the content in Form N-SAR and 2) to describe the merging process between Form N-SAR and the CRSP MFDB. We download 116,243 N-SAR Forms from the SEC EDGAR database. There are 133 information items reported in Form N-SAR. The central piece of information pertaining to our paper is the business relationships between mutual funds and their brokers: that is, the top ten brokerage firms that received the most commissions (Item 20) and the total brokerage commissions paid (Item 21).

The N-SAR reports are organized at the registrant level, which consists of one or more funds within a fund family, generally grouped together because of a common inception date (see Edelen et al. (2012)). Although Form N-SAR provides separate information for each individual fund, such as their TNA, it only discloses brokerage commission details at the registrant level. As an illustration, Table 4.6 provides a snapshot of N-SAR filing information for Fidelity Advisor Series I. In our example, Fidelity Advisor Series I is the registrant, consisting of 14 distinct mutual fund portfolios. It filed its Form N-SAR on January 31, 2008 for the six-month reporting period that ended in November 30, 2008. The total commission paid by these 14 mutual fund portfolios was approximately $\$43,376,000$. Goldman Sachs received $\$5,095,000$, the largest amount of commissions during this period among all brokers. The top ten brokerage firms contributed 76% of the total paid commissions. We point out one imperfection in our data is that we are not able to track down the precise timing of these commission payments. In addition, other registrants within the same fund family could have different filing dates. We follow Reuter (2006) to aggregate brokerage commission payments across individual funds within the same family. To do so, we first convert the half-yearly payments into monthly payments by assuming the commission payments were uniformly paid during the reporting period.

For each month, we add these monthly payments across all funds to estimate the total brokerage commission payments made by each mutual fund family to their brokers.

We merge Form N-SAR with the CRSP MFDB. Due to a lack of common identifiers between the two, we perform the matching based on fund names. To minimize matching errors due to fund name changes, our matching process is conducted at the fund-date level. We implement a battery of robustness checks by comparing the fund's TNA reported in both Form N-SAR and the CRSP MFDB. Specifically, we perform three comparisons: 1) between TNA in Form N-SAR (Item 74T) and TNA in the CRSP MFDB, 2) the six-month TNA average in Form N-SAR (Item 75B) and the six-month TNA average in the CRSP MFDB, and 3) the NAV in Form N-SAR (Items 74V1 and 74V2) and that in the CRSP MFDB. We require the reported discrepancies between the two databases to be no more than 10% for at least two of the three criteria. Table 4.7 compares between the CRSP mutual funds universe and the sample of funds that we are able to match with N-SAR Forms from 1999 onward. On average, matched funds are larger and older and have lower turnover ratios than non-matched funds. The number of matched funds and statistics are largely consistent with recent studies that also employ Form N-SAR.

Table 4.6: Example of form N-SAR.

This table displays the Form N-SAR filed by Fidelity Advisor Series I for the six-month reporting period ended in Nov, 30 2007. The registrant consists of 14 unique mutual fund portfolios, as indicated by the assigned series number. Form N-SAR provides the commission paid by the registrant to its top ten brokers during the six-month reporting period. The original form can be retrieved from `http://www.sec.gov/Archives/edgar/data/722574/000088019508000009/answer3785.fil`.

| | |
|---|---|
| **Period of report:** | Nov, 30 2007 |
| **Filed as of date:** | Jan, 31 2008 |
| | |
| **Registrant Name:** | Fidelity Advisor Series I |
| **File Number:** | 811-03785 |

**List the name of each series or portfolio:**

| **Series Number** | **Series name** |
|---|---|
| 1 | Fidelity Advisor Equity Growth Fund |
| 2 | Fidelity Advisor Large Cap Fund |
| 3 | Fidelity Advisor Mid Cap Fund |
| 4 | Fidelity Advisor Growth & Income Fund |
| 5 | Fidelity Advisor Strategic Growth Fund |
| 6 | Fidelity Advisor Growth Opportunities Fund |
| 7 | Fidelity Advisor Value Strategies Fund |
| 8 | Fidelity Advisor Small Cap Fund |
| 10 | Fidelity Advisor Equity Income Fund |
| 12 | Fidelity Advisor Dividend Growth Fund |
| 13 | Fidelity Advisor Dynamic Capital Appreciation Fund |
| 14 | Fidelity Advisor Fifty Fund |
| 15 | Fidelity Advisor Equity Value Fund |
| 16 | Fidelity Advisor Leveraged Company Stock Fund |

**List the top 10 brokers which received the largest amount of brokerage commissions:**

| **Name of Broker** | **Gross commissions received (in thousands of dollars)** |
|---|---|
| Goldman Sachs & Co. | 5,095 |
| UBS AG | 4,508 |
| Merrill Lynch & Co., Inc. | 4,125 |
| Credit Suisse Group | 4,086 |
| Lehman Brothers Holdings, Inc. | 3,596 |
| Morgan Stanley | 3,171 |
| Citigroup, Inc. | 2,657 |
| JP Morgan Chase & Co. | 2,066 |
| Deutsche Bank AG | 1,893 |
| Bank of American Corporation | 1,851 |
| **Total top 10 brokerage commissions** | 33,048 |
| **Total brokerage commissions paid** | 43,376 |

Table 4.7: Comparison between CRSP mutual funds and Form N-SAR matched mutual funds.

This table compares between the CRSP universe of mutual funds and the N-SAR matched mutual funds for the period between 1999 to 2012. We focus on actively managed domestic equity funds. We aggregate the TNA for all fund share classes. For expense ratio, turnover ratio, and fund age, we compute the TNA-weighted average across all fund share classes. Expense ratio is the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. Turnover ratio is the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month TNA of the fund. Fund age is the number of years since inception.

| | **CRSP mutual funds** | | | | | | **N-SAR matched funds** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Number of funds** | **Number of families** | **TNA** | **Expense ratio (%)** | **Turnover ratio (%)** | **Age** | **Number of funds** | **Number of families** | **TNA** | **Expense ratio (%)** | **Turnover ratio (%)** | **Age** |
| 1999 | 2149 | 333 | 1015.92 | 1.29 | 92.04 | 10.46 | 1277 | 310 | 1230.74 | 1.27 | 83.08 | 11.88 |
| 2000 | 2389 | 393 | 1149.33 | 1.31 | 99.45 | 10.32 | 1329 | 349 | 1410.60 | 1.27 | 94.98 | 11.35 |
| 2001 | 2470 | 407 | 876.78 | 1.33 | 112.69 | 10.51 | 1393 | 356 | 1079.04 | 1.30 | 101.83 | 11.62 |
| 2002 | 2521 | 403 | 743.38 | 1.37 | 113.18 | 11.03 | 1542 | 370 | 904.68 | 1.33 | 102.42 | 11.93 |
| 2003 | 2517 | 393 | 757.00 | 1.40 | 110.10 | 11.52 | 1536 | 360 | 883.55 | 1.38 | 99.52 | 12.24 |
| 2004 | 2488 | 387 | 936.94 | 1.38 | 97.40 | 12.01 | 1532 | 351 | 1143.54 | 1.36 | 88.66 | 13.04 |
| 2005 | 2454 | 369 | 1035.68 | 1.33 | 89.52 | 12.48 | 1470 | 330 | 1301.05 | 1.31 | 79.58 | 13.70 |
| 2006 | 2387 | 354 | 1168.31 | 1.29 | 86.42 | 13.02 | 1397 | 311 | 1428.39 | 1.26 | 78.28 | 14.15 |
| 2007 | 2324 | 337 | 1344.67 | 1.24 | 87.31 | 13.78 | 1398 | 299 | 1663.12 | 1.22 | 80.74 | 15.11 |
| 2008 | 2215 | 334 | 1091.21 | 1.20 | 88.82 | 14.94 | 1355 | 287 | 1236.69 | 1.19 | 84.17 | 15.67 |
| 2009 | 2085 | 315 | 994.58 | 1.22 | 103.41 | 16.25 | 1304 | 287 | 1166.83 | 1.20 | 96.79 | 17.21 |
| 2010 | 1903 | 305 | 1261.30 | 1.21 | 95.79 | 17.43 | 1206 | 273 | 1425.36 | 1.20 | 91.21 | 18.13 |
| 2011 | 1827 | 298 | 1421.14 | 1.18 | 84.36 | 18.38 | 1180 | 269 | 1651.21 | 1.16 | 76.35 | 19.06 |
| 2012 | 1719 | 276 | 1539.90 | 1.15 | 81.73 | 19.17 | 1071 | 247 | 1771.71 | 1.13 | 73.62 | 20.04 |

# Chapter 5

# Conclusion

This dissertation pursues research on three different fund segments: CEFs, hedge funds, and mutual funds. Chapter 2 empirically tests whether investors use CEFs as a vehicle to gain exposure to illiquid securities, as hinted in the theoretical paper by CSS. We find direct evidence in support of our conjecture: Institutional managers are more likely to invest in CEFs if the underlying securities are highly illiquid. Importantly, our study encompasses the U.K. CEF industry, whose features are distinct from those of the U.S. market, and our results turn out to be equally applicable to the U.K. market in general. Besides complementing the results of CSS, our paper highlights the inherent advantages of structuring an investment product into closed-end should the underlying securities be illiquid, as already observed in other market segments, such as REITs, listed private equities, and secondary market traded hedge funds.

Chapter 3 revisits the literature on hedge funds' use of options. Specifically, we show that the performance evaluation technique of Aragon and Martin (2012) is fundamentally flawed. Using an improved evaluation technique, we find that hedge funds' publicly disclosed option positions are not as informative as one might think they should be; a quarterly tracking portfolio of options based on these disclosed holdings generates significant negative monthly returns. We do not suggest our results are conclusive of hedge funds are not skilled in their derivative investments but, rather, we call for further robust evidence. Nonetheless, we see that the view where hedge fund derivative investments reflect "smart" money may be misguided.

Chapter 4 proposes an innovative new identification strategy to measure the capital value relationship between mutual funds and their brokers. We examine how the sudden collapse of Lehman Brothers in late September 2008 impacted its mutual fund clients' performance. In this setting, we hypothesize these mutual funds should suffer a drop in performance returns in the aftermath. Consequently, we interpret this as evidence that mutual funds derive significant value from maintaining a stable relationship with their brokers.

This dissertation is, of course, not without its limitations, which opens up opportunities for future research in these areas. In Chapter 2, despite the fact that CEFs are dominated by retail investors in the U.S., our analyses are constrained to institutional investors due to the inherent difficulty in obtaining holdings information on retail investors. Although we partially address this issue by looking at the U.K. CEF industry, which, in contrast, is heavily dominated by institutions, it is still possible for future researchers to utilize new data and revisit our results.

In Chapter 3, we rely on publicly available information on hedge fund option holdings from 13F filings. Hedge funds are lightly regulated and hence not required to report their short positions or the strike prices and time-to-maturity of their options. No doubt, the absent of such information significantly limits the insights researchers can obtain. While we do perform a battery of robustness tests to address these issues (the unavailability of strike prices and time-to-maturity), we recognize our performance evaluation technique is not perfect. Nonetheless, the objective of the paper is to point out the incorrect conclusion drawn in previous literature. We argue that granular data are essential examining how hedge funds trade their derivative securities and performance.

In Chapter 4, as many other mutual fund researchers, we focus exclusively on domestic, actively managed equity mutual funds. A natural extension is to examine the performance of bond funds in the aftermath. Unlike equity funds, bond funds primarily trade with dealers, who charge either a mark-up or mark-down spread on the transacted securities as a form of compensation. Given that these transactions are conducted on a principal basis, we would expect that a stable long-term relationship with the dealers plays a more vital role in bond funds than in equity funds.

We leave all these issues to future research work.

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