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Investment Skill Of Hedge Funds:
A Holdings-Based Evaluation

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Investment Skill Of Hedge Funds: A Holdings-Based Evaluation

by

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Dedicated to my wife Annu.

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Investment Skill Of Hedge Funds:
A Holdings-Based Evaluation

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The University of Texas at Austin, 2015

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In Chapter 1, I provide new compelling evidence that hedge funds possess investment skill. Using the longest-in-literature hedge fund sample with fewer biases, I show that large holdings of past winners earn 7% annual benchmark-adjusted return. This remarkable performance is consistent with the notion that large holdings represent managers' best ideas. My sample goes back to 1980 and does not miss non-surviving hedge funds, or those that do not voluntarily report to commercial databases. It consists of all investment managers that must report to the SEC, except those that I identify as managers other than hedge funds. While publicly available data is not sufficient to identify hedge funds directly, my "reverse identification" method achieves both high sensitivity and specificity. I also find weaker yet significant evidence of investment skill in standard indicators such as average fund performance and performance persistence. Additionally, I study the announcement effect of 13F holdings disclosure on the disclosed stock return and trading volume.

In Chapter 2, I provide new evidence on market timing by studying ETF option holdings of hedge funds. I find that market option holdings are economically significant in terms of their impact on the market exposure of the funds. Further, I find significant time variation in market option holdings, which could be due to market timing activity. I find that market option holdings are associated with such fund characteristics as active share and market exposure of the fund due to its stock holdings; this evidence is consistent with options being used for hedging. Increases in aggregate hedge fund industry holdings of market put options predict low market returns. In the cross-section of hedge funds, the top 5% group has market volatility timing skill that is distinguished from luck with a bootstrapping test. Additionally, I measure market timing ability as the average risk-adjusted return on market option holdings, which, due to data limitations, requires additional assumptions about option prices. I find that this market timing ability is close to zero for the average fund but it is negative for heavy option users.

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Chapter 1

Best Ideas of Hedge Funds[1]

In this Chapter, I provide new compelling evidence that hedge funds possess investment skill. Using the longest-in-literature hedge fund sample with fewer biases, I show that large holdings of past winners earn 7% annual benchmark-adjusted return. This remarkable performance is consistent with the notion that large holdings represent managers' best ideas. My sample goes back to 1980 and does not miss non-surviving hedge funds, or those that do not voluntarily report to commercial databases. It consists of all investment managers that must report to the SEC, except those that I identify as managers other than hedge funds. While publicly available data is not sufficient to identify hedge funds directly, my "reverse identification" method achieves both high sensitivity and specificity. I also find weaker yet significant evidence of investment skill in standard indicators such as average fund performance and performance persistence. Additionally, I study the announcement effect of 13F holdings disclosure on the disclosed stock return and trading volume.

[1] This chapter is based on a working paper coauthored with Parker Hund, who was an undergraduate student at the University of Texas.

1.1 Introduction

While active money management accounts for 80% of $58 trillion global assets under management, there is only scarce empirical evidence of investment skill. The average mutual fund generates benchmark-adjusted returns that are close to zero both pre-fee and post-fee, with little distinction between the two due to the small fees on the order of 1% a year (see e.g. Fama and French (2010)). In the cross-section of mutual funds, Carhart (1997) does not find performance persistence even at short horizons once momentum is accounted for. Rationalizing this, Berk and Green (2004) demonstrate that due to the fund flows, investment skill does not have to manifest itself through performance persistence. Therefore, it is interesting to look for evidence of investment skill in a setting where fees are higher and flows are restricted.

In this paper I evaluate the investment skill of hedge fund managers. With hedge funds, pre-fee returns are expected to be high because the high fees they collect firstly allow them to attract elite investment talent, and secondly create a large gap between pre-fee returns and post-fee returns, which are expected to at least match the benchmarks. Further, persistence of high pre-fee returns is more likely to be seen with hedge funds than other managers because they are able to restrict inflows, which are thought to degrade fund performance. To this end, large clients of hedge funds often negotiate restrictions on the amount of future inflows the manager may accept from other clients. Accordingly, some successful funds close for new clients.[2] These

[2] For evidence of flow constraints, see Citi's industry survey Citi (2011).

institutional features of hedge funds make it likely that investment skill will manifest itself in average pre-fee returns and performance persistence, which I examine in this paper.

In addition to evaluating the performance of hedge fund portfolios as a whole, I focus on the performance of large holdings in hedge fund portfolios. Due to performance-based compensation and co-investment requirements, the returns of the hedge fund represent a big part of manager's overall income. Therefore, the manager has incentive to diversify the fund and to maximize its Sharpe ratio, as opposed to maximizing alpha. Large concentrated positions in the portfolio reduce diversification and are likely to be held only if they offer higher expected returns. Another cost associated with large holdings is price impact of trading, especially for small and illiquid stocks. I conjecture that the large holdings of hedge funds represent their best ideas. I study the performance of these best ideas of hedge funds because I expect the best ideas to provide strong evidence of investment skill.

Several issues complicate hedge fund studies including limited data availability, difficulties in risk-adjustment of returns, and biases in hedge fund databases. Unlike mutual funds, hedge funds are not required by regulations to disclose their returns and holdings, with the exception of the 13F form discussed below. Many hedge funds voluntarily report to commercial databases. The reported data includes the latest descriptive information, the time series of after-fee returns, and the time series of assets under management, but does not include holdings. Using the reported returns to evaluate the skill of hedge fund managers is problematic. Due to the use of derivatives and time-varying leverage, returns are not normally distributed (Agarwal and Naik (2004)) and are, therefore, difficult to adjust for risk. Additionally, the returns are reported net of fees and therefore represent returns received by fund clients rather than returns generated by fund managers. Inferring pre-fee returns from post-fee returns is complicated because fees are individually negotiated with each client and high water mark provisions are individually applied to each client's assets.

Aside from returns issues, hedge fund databases are subject to survivorship bias and self-reporting bias. Survivorship bias is estimated at 3-5% annual return for the average fund (see Fung and Hsieh (2000); Ibbotson, Chen, and Zhu (2011)). Some major databases keep all dead funds since 1994 thus allowing for a survivorship bias free study, albeit in a relatively short time-period. Highlighting the non-transparent nature of proprietary databases, Aggarwal and Jorion (2010) find a 5% survivorship bias in 1994–2001 in TASS database, which was assumed to be without the bias since 1994 and was used by most academics. Self-reporting bias refers to the difference between funds that voluntarily report to databases and the funds that do not report. Employing different samples and methodologies to evaluate performance of non-reporting funds, recent papers find either no self-reporting bias (Agarwal, Fos, and Jiang (2013a); Edelman, Fung, and Hsieh (2013)) or a bias as high as 5% per year (Aiken, Clifford, and Ellis (2013)). I avoid these biases and issues with returns by studying only long equity holdings of hedge funds, which must be reported to the SEC in quarterly 13F filings. Two limitations of this approach are that I only examine a part of the hedge fund portfolio and I do not observe intra-quarter changes in holdings. However, these limitations likely introduce bias against my findings of hedge fund outperformance.

A key contribution of this paper is identification of hedge funds among all 13F filers in 1980-2013 in a way that aims to avoid survivorship bias. I am not the first to study 13F holdings of hedge funds. However the existing literature relied on hedge fund databases to identify hedge funds among 13F filers. This procedure limits survivorship bias free sample to the post-1994 period while 13F data is available since 1980. Identification of hedge funds using alternative sources, such as archived news articles, is likely to miss hedge funds that performed poorly and were liquidated. I ensure that all dead hedge funds are kept in the sample by starting with all 13F filers and only removing the filers that I identify as institutions other than hedge funds. This "reverse identification" approach keeps in the sample some non-hedge-fund filers that I was not able to classify, but does not introduce a palpable survivorship bias.

There are two concerns with my sample construction methodology. First, the sample might include so many unclassified non-hedge-fund firms that it is not representative of hedge fund performance. Second, I am more likely to keep a non-hedge-fund in my sample if it performed poorly and died early, because less data is available for classification earlier in the sample. This introduces a bias in my sample that is opposite to the survivorship bias. I address these concerns by thorough classification that relies on archived news articles and print directories of money managers. I identify a variable that can be found for most firms even early in the sample and is useful in screening non-hedge-funds. Specifically, in the pre-1995 period I am able to drop many non-hedge-funds from my sample because most of their assets under management were provided by pension fund clients, which were restricted in their hedge fund investments by ERISA regulations. The pension assets variable is not helpful for direct identification of hedge funds and therefore it has not been used in the literature. As a result, my classification achieves high specificity. Only 7% of my sample are firms which I am not able to classify as either non-hedge-funds or hedge funds. To my knowledge, I am the first to construct a pre-1994 hedge fund sample without a palpable survivorship bias and a 13F sample designed to include all hedge fund firms. My sample spans over three decades of observations, 1980–2013, sufficient to detect the typical magnitudes of risk-adjusted performance.

I find economically and statistically significant evidence of hedge fund manager skill. The average fund earns 1.8% annual four-factor alpha on the long domestic equity part of its portfolio. The alpha, when leveraged, is economically significant and is comparable to total hedge fund fees. Funds in the top quartile of past one year performance continue to outperform with annual alpha of 3.9%. While best ideas of the average fund do not outperform, best ideas of best funds outperform both the benchmarks and the rest of their portfolios. The portfolio that holds the best ideas of top quartile funds generates four-factor alpha of 7.0% per year with t-statistic of 3.7. I show that performance of best ideas of best funds is statistically and economically distinct from the performance persistence of complete portfolios.

The rest of the paper is organized as follows. In Section 1.2 I provide literature review and discuss my contribution. In Section 1.3 I describe data sources and sample construction. In Section 1.4 I briefly discuss the three testing methodologies employed throughout the paper. In Section 1.5 I discuss the main empirical results. In Section 1.6 I study the announcement effect of 13F disclosure. In Section 1.7

I report results of robustness tests. In Section 1.8 I explore extensions including best ideas of mutual funds and an implementable trading strategy. In Section 1.9 I summarize and conclude.

1.2 Literature Review and Contribution

This paper contributes to the literature on performance of institutional investors. A number of papers[3] find strong outperformance by hedge funds even after fees. However, these findings are based on data in hedge fund databases and are, therefore, subject to a number of biases and issues in risk-adjustment of returns. Studying 13F holdings of hedge funds, Griffin and Xu (2009) provide evidence that the skill of hedge funds is much more modest than previously understood. They demonstrate that there is only marginal evidence of pre-fee outperformance and performance persistence. They also show that large holdings of hedge funds only marginally outperform large holdings of mutual funds and do not outperform other holdings of hedge funds. I build on their methodology by doubling the sample length and by further addressing sample biases. Additionally, I find evidence of skill in the "best ideas of best funds" effect, which is distinct from performance persistence and performance of large holdings.

In their working paper, Cohen, Polk, and Silli (2010) find that best ideas of mutual funds outperform. Their definition of best ideas is more nuanced[4] than

[3]E.g. Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Kosowski, Naik, and Teo (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Fung and Hsieh (2011), Ibbotson et al. (2011)

[4]They first define the best idea of a mutual fund as one stock in the portfolio that has the highest

mine and it selects stocks with small size and high idiosyncratic volatility, which are characteristics known to be associated with abnormal returns. In addition to studying a different type of investors, I define best ideas simply as large portfolio holdings and thus avoid the issues in risk adjustment of returns.

A closely related sample construction methodology is employed by Agarwal et al. (2013a), who use archived news articles in addition to hedge fund databases to identify hedge funds in 13F. However, their procedure is still subject to the survivorship bias because both the databases and the press coverage of hedge funds are biased. Further, unlike the present paper, Agarwal et al. (2013a) limit their analysis of fund performance to the difference between self-reporting and non-reporting funds. The same sample of hedge funds is also used in Agarwal, Jiang, Tang, and Yang (2013b) to study *confidential* 13F filings, which are supplemental 13F filings covering a part of the portfolio and individually approved by the SEC to be disclosed with an additional delay, typically, up to one year. They find that confidential filings outperform regular filings of the same filer by annualized 4.99% in the first quarter. The Thomson Financial 13F holdings database does not include confidential filings. The effect of this omission on my study is a potential underestimation of hedge fund returns on their domestic equity portfolio. This effect is likely small because only 6% of hedge fund 13F filings are confidential and in most cases they account for less than 25% of the portfolio value.

More recently, working papers Chen, Da, and Huang (2015) and Jiao, Massa,

product of weight, adjusted for a benchmark, and idiosyncratic volatility. They then select best ideas that have the product in the top quartile across all mutual funds.

and Zhang (2015) relate aggregate 13F holdings of hedge funds to the aggregate short interest. They find that changes in aggregate ownership, short interest, and their net strongly predict next quarter stock returns, albeit in hedge fund samples that are subject to survivorship bias. In their study of hedge fund crowding, Sias, Turtle, and Zykaj (2015) employ a survivorship bias free proprietary list of hedge funds identified among 13F filers by Thomson Financial in 1998–2012. They find that the number of a stock's buyers net of sellers predicts its high return, however their panel regression inference does not account for cross-sectional correlations. Cao, Chen, Goetzmann, and Liang (2015) study the relationship between a stock's mispricing and its hedge fund ownership. They find that the portfolio of stocks with high lagged alpha and high hedge fund ownership generates alpha, but there is no alpha when hedge fund ownership is low. Their sample of hedge funds spans 1981-2012, but it is subject to survivorship bias. Jame (2015) uses ANcerno trade execution data on hedge funds to relate their returns and liquidity provision. From the perspective of the present paper, the advantages of ANcerno data is that it has high frequency and that sale transactions include short sales, albeit short sales are not identified. The limitations of the data are that the hedge fund sample is small, only 71 firm, and not representative along some fund characteristics; and that holdings can only be approximated by cumulating trades over time. Jame (2015) finds that the portfolio tracking hedge fund trades earns abnormal return, but the portfolio tracking holdings does not.

1.3 Data Sources and Sample Construction

Tests in this paper are based on holdings data. Hedge funds neither disclose their holdings to databases nor to their own investors. However, all large investment managers are required by the SEC to disclose their long domestic equity holdings in quarterly 13F filings. The filings do not identify the type of the investment manager, e.g. whether it is a hedge fund or a traditional separate accounts manager. Identifying hedge fund managers using hedge fund databases or news articles introduces survivorship bias because of increased coverage of hedge funds over time. Instead, I start with the full sample of 13F filers, and while I do attempt to classify each filer as a hedge fund or not a hedge fund, I keep in the sample all the firms about which I am not sure. This approach allows for further refinements of the sample and I now have relatively few firms that are not definitively classified.

I start with the full sample of 13F filers in 1980-2013 compiled by Thomson Financial. The database does not have a permanent firm identifier and the same firm is often assigned a new identifier after a temporary break in reporting, change of name or firm's ownership changes that were not consequential to the firm's business, client composition, or assets under management. I use the permanent identifier of managers in Thomson's 13F database constructed by Brian Bushee.[5] The number of distinct firms in the full 13F sample is 5781. The filers are classified by Thomson Financial as banks, insurance companies, investment management companies (mutual funds) and their managers, other investment advisors, and all others, such as internally managed

[5]I am grateful to Brian Bushee for maintaining the identifiers and making them available on his website http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

pension funds and endowments. Thomson Financial maintained the classification only until 1999 and Brian Bushee has maintained it since then. Hedge funds fall under the definition of investment advisors because they primarily engage in securities trading on behalf of a client for a fee and are not investment management companies. There are 4229 investment advisors in the sample.

In the sample of investment advisors I classify the firms as either hedge funds or advisors other than hedge funds, or advisors that I am not able identify. For this classification I first attempt to find form ADV on the SEC website. With certain exemptions, large investment advisors are required to file form ADV with the SEC on the annual basis. The most recent ADV form is available on the SEC website if it was filed within the last ten years and unfortunately I am not aware of any source of ADV data prior to that. Since 2011 the form ADV lists all hedge funds managed by the filing investment advisor and their total assets which makes the identification straightforward. Prior to 2011 the ADV data includes client count breakdown by client type with pooled investment vehicles being one of the types, whether a performance fee is charged, and the list of all private funds, that may or may not be hedge funds, with their assets. I identify an ADV filer as a hedge fund if all clients are pooled investment vehicles, a performance fee is charged, and the private funds account for most of assets. I identify an ADV filer as not a hedge fund if it has no pooled investment vehicle clients, or if it does not charge performance fee, or if private funds account for less than half of total assets of the firm. Using data in forms ADV I classified 3121 firms. Out of them, 809 are hedge funds and 2312 are not hedge funds.

For the 1988-2002 period I primarily rely on the Nelson's Directory of Investment Managers, available only in print prior to 2000 and on CD in later years. The level of detail in the Nelson's data increases over time. Post-1992 editions often provide information on various investment products offered by the investment advisor, such as separate accounts, mutual funds, managed funds, limited partnerships, or even explicitly hedge funds. I found that hedge fund firms that provide information to Nelson's Directory often do not explicitly classify themselves as hedge fund firms, and provide very limited information, making the Directory useful for identifying non-hedge-fund firms rather than hedge funds firms directly.

The variables that I found populated for most firms are the asset breakdown by client type, whether most assets are managed via separate accounts or pooled funds, and whether a performance fee is charged on most assets. Client types include corporate pensions, unions, endowments, insurance companies, individuals, and mutual funds. In the pre-1995 period I identify as non-hedge-fund firms those that manage most of their assets for pensions, unions, and endowments. Historically tax-exempt investors were restricted from investment in hedge funds due to fiduciary responsibility. According to the ERISA regulation, a pooled fund manager has to assume fiduciary responsibility if 25% of the fund's assets are provided by pension funds. I rely on pension and endowment clientele variables in my classification only in pre-1995 period because it is uncontroversial that tax-exempt institutions did not invest in hedge funds until the second half of the 90s. David Swensen at the Yale University endowment pioneered hedge fund investment by endowments and pension funds joined the practice later.

In the 1980s I find the data on the fraction of assets that are managed for pensions and other tax-exempt institutions in annual print editions of the Money Market Directory. Throughout the sample period I supplement the classification data sources with archived news articles on Factiva. My final sample consists of 1154 firms, out of which 1079 are hedge fund firms and 75 are the firms that I am not able to definitively classify.

Table 1.1 shows the sample size by year. I further apply relatively non-restrictive screens. I require the firm to have at least 5 domestic equity holdings and at least 50% of 13F assets in domestic equity.[6] I exclude firms that report 13F assets below $10 million. Table 1.1 also reports the number of hedge funds that have holdings data available in the previous four quarters. This subsample is used in performance persistence tests. Table 1.1 additionally reports the number of funds that have large holdings. This subsample is used in the best ideas tests. Also reported is the number of funds that have both the holdings data history and large holdings. This subsample is important when I test best ideas of best funds. My sample is thin for the 1980s. A thin sample does not introduce bias but can lower t-statistics. Additionally, in performance persistence tests I need to further split the sample based on past performance. For this reason, I report some of the results both for the full sample and for the post-1985 sample.

Figure 1.1 shows how my sample size compares to sample sizes in related

[6]The list of securities that must be reported in 13F, in addition to domestic equity, includes some fixed income, options, or non-domestic securities. However, the list is not comprehensive. I only use domestic equity holdings.

studies that also use 13F filings of hedge fund managers. Griffin and Xu (2009) obtain hedge fund names from several databases, primarily from AltVest, Mar, Nelson's Directory, and TASS, and match these names to 13F filings. Ben-David, Franzoni, and Moussawi (2012) and Ben-David, Franzoni, Landier, and Moussawi (2013) use a proprietary classification used internally by Thomson Financial that identifies hedge fund firms among all 13F filers. The overall size of my sample is close to these benchmarks. However, there are important differences in year-by-year comparison. The differences in sample sizes over time are due to the definition of what is a hedge fund firm, namely what should be the percentage of assets managed by the firm via hedge funds to be classified as a hedge fund firm. In the sample construction I require that over 50% a management company's assets are in hedge funds. Ben-David et al. (2012) explain that Thomson Financial maintain an internally used classification of all 13F filers that takes into account the asset composition by the type of the management business. More specific details are not disclosed, however. Griffin and Xu (2009) verify that most firm's assets are in hedge funds only for a subset of firms. For other firms they only verify that most of a firm's clients are pooled investment vehicles or wealthy individuals according to form ADV. These criteria do not exclude traditional wealth managers that manage most of the wealthy individuals' assets in separate accounts but also have a smaller investment product that charges a performance fee. In cases when form ADV is not available, I also excluded firms that in the pre-1995 period managed most of their assets for tax-exempt institutional clients. These differences in identification of hedge fund firms explain the sample size differences.

I include robustness tests that use two alternative samples. One of the alternative samples is my main sample but only in the post-2000 period where I primarily relied on ADV data. The second alternative sample is based on Morningstar CISDM hedge fund database in the 1994–2013 period. The database was extensively used in the hedge fund literature and is survivorship bias free since 1994. Like all hedge fund databases, CISDM is primarily a fund-level database and does not provide information on whether most of assets of the managing firm are hedge fund assets. It is also subject to the self-reporting bias. These considerations and the shorter time-period are the reasons that I use the hand-collected sample for the main results.

1.4 Testing Methodology

Throughout the paper I evaluate performance of managers using three standard testing methodologies. In the first type of tests, I construct a single calendar-time portfolio, which I also refer to as a "strategy" portfolio. The portfolio pools together all hedge funds or individual stocks that I want to test for outperformance, thus generating a single time-series of returns. Next I evaluate a benchmark-adjusted performance of this portfolio, e.g. using a factor model. I then make conclusions about the group of stocks based on performance of the pooled portfolio. Throughout this paper the calendar-time portfolios are equal-weighted and rebalanced monthly. One advantage of this methodology is that it yields a conservative estimate of t-statistics. Another advantage is that the strategy portfolio can be constructed in practice and thus represents a tradable strategy. A disadvantage of this methodology is that on every calendar date it pools many observations of returns of individual stocks in one observation of return of the portfolio. This loss of information results in loss of test power compared to other statistical tests that use individual stock returns.

In the second type of tests I construct long-short strategy portfolios. The long-short portfolios are long one pooled calendar-time portfolio and short another. I use long-short portfolios to test whether the long portfolio performs significantly better than the short portfolio. For such a comparison, I could instead estimate alphas of both portfolios and then compare them. However, the advantage of a long-short test is that it allows me to partially control for risk-factor exposures beyond the standard factors. Controlling for non-standard sources of risk is especially important when evaluating performance of hedge funds because they actively exploit market anomalies.

The third type of test that I employ in this paper is the Fama-MacBeth cross-sectional test. The advantage of the Fama-MacBeth test compared to calendar-time portfolio tests is that it allows me to compare predictive powers of multiple stock characteristics in one test. This methodology also allows me to evaluate the predictive power of stock characteristics that are not discrete, such as the ownership of the stock by a hedge fund, but are continuous, such as the weight of the stock in a hedge fund portfolio. Fama-MacBeth estimation also pools the cross-sectional information when estimating the t-statistics and thus represents a conservative test.

In addition to the standard four factors, in the tests I include a liquidity factor. Controlling for liquidity is important because hedge funds heavily invest in illiquid stocks. I use the traded liquidity factor from Pástor and Stambaugh (2003a) available on the WRDS website.

1.5 Performance Results

1.5.1 Performance of the Average Hedge Fund

I start the investigation of hedge fund skill by evaluating the performance of the average hedge fund. First I use the calendar-time portfolio methodology. Every month the portfolio invests equally in all sample hedge funds, thus the portfolio return is representative of the return of the average hedge fund. More specifically, the hedge fund portfolios I mimic are long domestic equity portfolios as reported on the form 13F as of the latest quarter-end. Here I aim to approximate manager's returns from these long positions and therefore I do not account for the 45-day gap between the quarter-end and the public availability of the 13F form.

The factor-adjusted performance and factor loadings of the average fund are presented in Table 1.2. Alpha estimates are similar across all three models even though factor loadings are significant. In the four-factor model the effect of size factor on alpha is balanced by the opposite effect of momentum factor. Liquidity factor is statistically significant and does reduce alpha but only slightly. While size and momentum factors cancel each other in their directional effect on alpha, together they increase explanatory power of the model and reduce error in the estimate of alpha making it statistically significant. CAPM alpha is insignificant while four-factor model and the model with liquidity yield significant and marginally significant alphas. The insignificance of CAPM alpha is due to the low magnitude of the average performance and the exposure to other factors.

As expected, the loading on the SMB factor is positive. Hedge funds on average do not seem to load on the value factor even though one would expect a tilt towards growths stocks where valuations are less certain and information advantage might matter more, which would result in a significant negative factor loading. More interesting is the significant negative factor loading on the momentum factor. This shows that on average hedge funds are contrarian investors, as opposed to mutual funds who are, on average, momentum investors. However, the factor loading of -0.04 is small in magnitude compared to the 0.11 loading found for the average mutual fund by Daniel, Grinblatt, Titman, and Wermers (1997). Loading on liquidity factor is positive and significant in agreement with previous empirical findings that hedge funds hold less liquid stocks taking advantage of the constraints placed on outflows through lock-up and redemption notice agreements as documented in Aragon (2007).

The estimated alpha, when levered-up, is comparable to the typical hedge fund fees. Using a commercial hedge fund database Ibbotson et al. (2011) estimate average realized annual fee of equity hedge funds to be 4%. This is higher than my estimate of alpha, however I have not yet accounted for leverage. Equity hedge funds achieve leverage by creating a short portfolio and using the short-sale proceeds to increase their long portfolio. The typical portfolio sizes are 50-100% of AUM in short portfolio and 150-200% of AUM in long portfolio. My estimate of alpha is based on the long portfolio assets, and due to leverage it translates to alpha on clients' assets that is 150-200% times the estimate. If I further assume that hedge funds generate alpha on short portfolio that is similar to long portfolio alpha, then alpha on clients' assets is 200-300% times my estimate. Therefore, the levered alpha, which the clients receive, is comparable to the fees.

My estimate of alpha is lower than estimates in studies relying on returns in hedge fund databases. Studies that rely on commercial databases find alphas of 3-5% per year (e.g. Fung and Hsieh (2011) and Ibbotson et al. (2011)). These estimates use returns received by hedge fund clients meaning that they are after fees and are levered. In contrast, I only find alpha that after levering approximately compensates clients for the fees, but does not leave significant post-fee return. The difference in estimates might be due to multiple reasons. I study performance in a longer sample period which is twice as long. On the other hand I only capture returns on domestic equity part of the portfolio. As already discussed, adjusting hedge fund returns is a challenge and database biases are a concern. Overall, my methodology and the resulting estimates are more conservative.

I further evaluate the stock selection skill of hedge fund managers in Fama-MacBeth framework. This methodology allows me to evaluate the predictive power of stock characteristics that are continuous, such as weight of the stock in a hedge fund portfolio. Table 1.3 shows the results of the cross-sectional test of stock return predictability using three measures of ownership of the stock by the hedge fund industry. In the first specification the explanatory variable is the dummy of ownership of the stock by at least one fund. This specification is similar to the calendar-time portfolio test where the same dummy is the criterion for inclusion of the stock in the portfolio, except the weighting of stocks is different. The cross-sectional regression yields alpha estimate similar in magnitude and significance to the estimate in the calendar-time portfolio test. The second specification employs the hedge fund ownership measure that is the fraction of hedge funds owning the stock. Intuitively, if hedge funds have skill then the more funds hold the stock the better the stock performance should be. The estimated positive loading on this ownership measure confirms the intuition however it is not statistically significant. In the third specification I use another measure of hedge fund ownership that is the weight of the stock in the aggregate portfolio of hedge fund industry. However, in this specification the intuition for positive loading is countered by the indexing consideration. If many funds partially index their portfolio to a broad market or to an industry then large stocks get large weights. Indexing consideration does not predict stock return but it does make the stock's weight less correlated with the stock's alpha. Accordingly, I find the loading on this ownership variable to be statistically insignificant.

Overall, I find economically and statistically marginal evidence of risk-adjusted performance of the average hedge fund before fees. However, when leverage is taken into account, the magnitude of the performance is economically significant and is roughly consistent with fees charged by hedge funds. My finding of close to zero post-fee returns is different from 3-5% annual post-fee alphas found by studies that rely on commercial databases that suffer from biases. I also find that the average fund holds small and illiquid stocks and is a contrarian investor in sharp difference to mutual fund behavior.

1.5.2 Performance Persistence

As discussed in the Introduction, the investment skill of hedge funds is likely to manifest itself through performance persistence. To test for persistence, every month I sort hedge funds in quartiles of past performance based on previous twelve month Sharpe ratio. I then form an equal weighted calendar-time portfolio that holds top quartile funds for one month, and is then rebalanced. Performance of the portfolio is reported in Table 1.4. The hedge fund sample is thin in the pre-1985 period (see Table 1.1). For this reason, I estimate performance for the top quartile in the post-1985 sample and also estimate performance for funds in the top half in full sample. I find statistically and economically significant alpha both for top quartile and top half funds. Funds that had below-median past performance exhibited no alpha, which is also consistent with performance persistence. The estimates for above-median funds are consistent in both samples. Performance of below-median funds is worse than performance of all funds discussed above, performance of above median funds is better than the average, and performance of the top quartile is better than performance of the top half. The differences between the top quartile and above median and between below-median and average are not likely to be statistically significant. However, the difference between the top half and the average is statistically significant which I formally confirm. I construct a long-short portfolio that is long the holdings of the best past performers and short the holdings of all sample funds. Table 1.5 shows that performance of the best funds is statistically distinct from performance of the average fund. The return generated by top quartile funds is 2.5 times higher than the industry average and is sufficient to cover hedge fund fees and provide after-fee return for the hedge fund clients.

As demonstrated in Table 1.6, the cross-sectional test of persistence confirms the findings of the portfolio tests. I further explore alternative measures of stock ownership by best funds. The fraction of best funds holding the stock appears to be a significant predictor of the stock's performance. However, this measure of ownership does not have any additional predictive power beyond the predictive power of the stock being held by at least one hedge fund.

1.5.3 Best Ideas

Stocks that have big weight in a manager's portfolio are likely the stocks that the manager estimates to have the highest alpha. This result comes from the portfolio optimization problem where a manager maximizes the Sharpe ratio of a portfolio of stocks. Treynor and Black (1973) study the maximization of portfolio Sharpe Ratio under the assumption that stock returns follow a market model. They show that the optimal portfolio weights are proportional to the stock's information ratio, which is the ratio of alpha to idiosyncratic volatility, $w_i \propto {}^{\alpha_i}/_{\sigma^2(\epsilon_i)}$. The result is generalized to multifactor models in Cvitanić, Lazrak, Martellini, and Zapatero (2006). If managers were maximizing only alpha of the portfolio then they would only hold one stock about which they have the most conviction. But managers likely maximize Sharpe ratio rather than alpha due to their personal exposure to portfolio risk. Their compensation is highly sensitive to performance and therefore portfolio risk translates to compensation risk. Additionally, managers may be required to co-invest to have skin in the game. Further, in order to avoid conflicts of interest, managers are restricted in trading on their own account.

In this paper I define a best idea of a hedge fund manager as a stock that has higher than 5% weight in his portfolio. According to this definition, a manager can have several best ideas. The threshold of 5% is relatively arbitrary but is justified by the following considerations. First, weights of below 3% might occur even in passive indexing portfolios, for example Apple in the S&P500 index. Second, significantly higher than 5% weights are rare enough to make my sample of best ideas too small, especially in the first half of the sample where there are not as many hedge funds. I do not measure the weight relative to a benchmark, such as S&P500, because I do not know what the appropriate benchmark would be for each particular fund. Using the market index as a benchmark does not seem to be appropriate because hedge funds market themselves as alternative investments and are not expected to be correlated with the market. Using inappropriate benchmark would introduce noise to the definition of hedge funds and bias the definition towards small stocks. Therefore, I do not adjust weights for a benchmark.

The calendar-time portfolio test I use for best ideas evaluates alpha of the portfolio that holds all stocks that are best ideas of at least one hedge fund. Results of the strategy portfolio test are reported in Table 1.7. In the full sample, the best ideas have alpha that is economically significant but only marginally statistically significant. For comparison I conduct the same test for all other holdings of hedge fund excluding the best ideas. The alpha of best ideas is not economically or statistically different from alpha of complete portfolio of the average fund or alpha of equal weighted-portfolio of all smaller holdings.

I now interact persistence and large holdings to find strong evidence that at least some managers have skill in picking at least part of their portfolios. Results of the portfolio test are reported in Table 1.8. Due to double screening on past performance and on size of holdings, my sample is thin in the pre-1985 period as shown in Table 1.1. Therefore I report most of the results for the post-1985 period. The alpha of best ideas of funds in the top quartile of past performance is economically high. For the above median funds the performance of best ideas is slightly lower but still economically and statistically high. Best ideas of funds with below median past performance have zero alpha but yet do not exhibit worse performance than their complete portfolios discussed in the performance persistence section.

The results of the long-short test and the cross-sectional test in Table 1.9 and Table 1.10. The results show that the performance of best ideas of best managers is strong enough to be statistically and economically distinguished from performance of the average fund, performance persistence, and performance of complete portfolios of the best funds that have best ideas.

1.6 Announcement Effect of 13F Filings[7]

Successful investors are closely watched by the investment community and by the media for clues on profitable investments. Analysis presented in this Section 1.8.2 shows that an implementable strategy that copies investment decisions of successful hedge funds based on their 13F disclosure generates significant abnormal returns before trading costs. There are two currently traded ETFs that passively implement just such a strategy that identifies best hedge funds based on past per-

[7] I thank Donghyun Kim for his help in linking the SEC EDGAR database and the Thomson Financial holdings database, which was required to obtain 13F disclosure dates for this chapter. Donghyun was a PhD student at the University of Texas.

formance and buys their large portfolio holdings as soon as they are disclosed in 13F filings. If 13F disclosure indeed reveals information about future returns of the disclosed investments, a change in the stock price might be observed around the disclosure date. Even if the disclosure is not informative about future returns, the fact that it is perceived as informative results in portfolio adjustments by the followers generating access trading volume and price-pressure returns. In this section I study the announcement effect of 13F disclosure in stock trading volume and stock return.

The announcement effect of hedge fund 13F disclosure is also studied in a working paper Brown and Schwarz (2013). They find positive abnormal volume prior to the announcement and after a few days following the announcement, but no abnormal volume on the announcement or during a few days following the announcement. In their preliminary examination of announcement returns, which does not seem to account for cross-sectional correlations or for disclosure clustering, they find positive equal-weighted market-adjusted average return on the date of announcement and during the following two days. I contribute to this research by examining the announcement effect of the best ideas of best funds as motivated by the present paper. My inference is more conservative as I employing a hedge fund sample with fewer biases and account for a general pattern of correlations in a panel regression with robust standard errors.

1.6.1 Announcement Effect in Volume

In this subsection I evaluate announcement effect of 13F filings as observed in the trading volume of the stocks on the 13F. Table 1.15 presents the volume effect results. Log volume is used as a dependent variable because its distribution has been shown to be approximately normal, unlike volume itself. The test is set up as a panel regression because an event study is inappropriate due to overlaps in dates of disclosure events. The dependent variables are lags and leads of one of the measures of disclosure type and intensity. Stock-quarter fixed effects are included so that the disclosure effect represents percent deviation of volume from its quarterly mean. Date fixed effects ensure that the coefficient estimates are not biased due to omission of common factors such as market volatility. Two-way clustered standard errors account for autocorrelations and same-date cross-correlations.

The results indicate that trading volume is lower than the quarterly average on the date of 13F disclosure and, in some subsamples, on the day before the disclosure. The volume is significantly higher a few days before the disclosure. This pattern is consistent with hedge funds trading more actively before their holdings are publicly known. These effects are stronger for best performing funds, and even stronger for the best funds disclosing large holdings or large changes in holdings.

1.6.2 Announcement Effect in Return

In this subsection I evaluate announcement effect of 13F filings as observed in the announcement returns of the stocks on the 13F. Table 1.16 presents the return effect results. The test is set up as a panel regression of DGTW adjusted returns on leads and lags of a disclosure variable. Because stock returns are cross-correlated not only on the same date but also on different dates, I calculate Driscoll-Kraay spatial correlation robust standard errors. They account for arbitrary correlation between any two errors within 22 days of each other and assume zero correlations for more distant errors. These errors have the advantage over clustered standard errors in that they do not assume zero correlation near a fixed cluster boundary.

The table presents results in four panels. Results in each panel are based on the full sample of stock-date observations. The difference between the panels is that the disclosure variable is multiplied by dummies for the disclosure by the best fund, the disclosure of large portfolio holdings, and the disclosure of large portfolio weight changes. While not robust across measures of disclosure, results generally indicate higher returns on and after the date of the disclosure. Coefficients in the first regression in Panel A indicate abnormal returns two and three days before the disclosure. However, this effect is not observed in any other specifications. There is evidence of abnormal positive returns one day before disclosure of large holdings and large holdings changes by the best performing funds. This is consistent with the holdings information leakage shortly before public disclosure.

1.7 Robustness Tests

I test whether my findings are time consistent by performing the main tests in the 1985-1999 and 2000-2013 periods. I do not include the years prior to 1985 in the sample because Table 1.1 shows they have fewer than 20 hedge funds. Table 1.13 shows results in the subsamples. The alphas in the early half of the sample disappear in the market model, but when the four-factor adjustment is done the results are consistent across the subsamples. The results also show that the performance of hedge funds has not deteriorated over time, in fact I find evidence of improvement in performance of the average fund as well as stronger performance persistence.

I also test my results on an alternative sample. The alternative sample consists of firms that appear in Morningstar CISDM hedge fund database that also appear in the 13F database. I only use the time-period since 1994 for which CISDM is without survivorship bias. In this sample I have not verified that most assets of the firm are in hedge funds. Therefore, the sample contains some firms that offer some hedge funds to their investors but manage most of the assets through arrangements other than hedge funds, e.g. mutual funds or separate accounts. The results for the alternative sample are shown in Table 1.14. The results generally agree with the main sample but are weaker. A possible explanation for weaker results is that the sample contains firm that are not hedge fund firms and they do not perform as well as hedge fund firms.

In yet unreported results, I confirm that my main findings hold when returns are adjusted using DGTW benchmarks. The main results also hold when the best ideas are defined based on adjusted portfolio weights. I adjust portfolio weights by subtracting the stock's weight in the value-weighted portfolio of all stocks in the CRSP universe.

1.8 Extensions

1.8.1 Comparison to Mutual Funds

Because hedge fund managers are better compensated than mutual fund managers, I expect that the hedge fund industry attracts better talent than the mutual fund industry. Moreover, mutual fund managers are more restricted in their investment even within long domestic equity strategies because they have to follow their stated investment policies and cannot use short positions to hedge their risks. In this section I examine evidence of skill among mutual fund managers using the same tests I use for hedge funds, allowing me to compare the skill of mutual funds to the skill of hedge funds.

To make mutual fund tests comparable to my hedge fund tests, I study returns on reported holdings of mutual funds disclosed in forms N-30D even though total returns are available in databases without major biases. One difference from the hedge fund setting is that in the 1985–2004 period many funds disclose their holdings on semiannual rather than quarterly basis. I still study the holdings-based returns that are within one quarter from being held by the fund, but I use actual complete returns when estimating past Sharpe ratio for sorting on performance. While 13F filings are on the management firm level, N-30D filings are on the individual fund level. I use N-30D data instead of 13F data for mutual funds because mutual fund firms are much bigger and offer a wide variety of funds following different strategies and managed by different managers. Since holdings of all the funds of a mutual fund firm are pooled together in 13F filings, the reported portfolio is likely to resemble market index. Additionally, mutual fund studies typically use the N-30D holdings so I do the same for results to be comparable. Griffin and Xu (2009) provide the same arguments when comparing performance of hedge funds based on 13F holdings to performance of mutual funds based on N-30D holdings.

Table 1.11 summarizes results of mutual fund performance tests and best ideas tests. The average mutual fund has risk-adjusted returns very close to zero which is evidenced not only by statistical insignificance but by the magnitude of alpha as well. The zero performance before fees translates to negative after-fee return. There is statistically significant evidence of mutual fund performance persistence, at least before fees, but the economic magnitude is quite small when factors beyond the market are included. The performance of best ideas of mutual funds is insignificant. Unlike the case of hedge funds, the best ideas of best mutual funds do not perform significantly better than complete portfolios of best mutual funds. Due to noise in alpha estimates, statistically significant difference between hedge funds and mutual funds should not be expected when comparing performance of the average funds and performance persistence. However performance of best ideas of hedge funds is strong enough to be distinguished from performance of best ideas of mutual funds. This demonstrates the power of the best-of-best test in detecting investment skill.

1.8.2 Implementable Trading Strategy

I have demonstrated that hedge fund managers, particularly those with the best past returns, are able to identify stocks with significant risk-adjusted returns. This shows a certain degree of market inefficiency because some of the most skilled professional investors are able to identify instances of mispricing. In this section I take this a step further by showing that an uniformed investor can generate economically significant risk adjusted returns by simply following the 13F filings of the best managers after they become public and buying their big holdings.

I construct a tradable strategy that holds the best ideas of the best managers while allowing for a two-month gap between the quarter-end and the public availability of 13F filings. Results in Table 1.12 show that the implementable best-of-best strategy generates economically significant profits. I do not estimate the costs of portfolio rebalancing but note that significant portfolio rebalancing is done only quarterly. Moreover, the strategy does not involve shorting, which can make a strategy non-implementable or non-profitable. This demonstrates that an implementable strategy that buys the best ideas of the best managers with a two-month delay also generates significant returns, providing evidence of market inefficiency.

1.8.3 Comparison of 13F Holdings-Based Returns with Total Returns

In this section I evaluate how representative are the 13F holdings-based returns, which are used throughout the study, about *true* returns on the complete hedge fund portfolio. I obtain true fund returns from BarclayHedge hedge fund database. The database returns are on the fund level so I calculate firm returns as value-weighted returns of the firm's funds. I determine the investment strategy of the firm based on reported strategies of the firm's funds and the funds' assets under management. The database returns are net of all fees.

Table 1.17 presents the correlation between holdings-based returns and true returns, explanatory power of holdings-based returns with respect to true returns, and the intercept from the regression of one on the other. The results are presented for a variety of subsamples based on firm investment strategy and two AUM-based filters. The first filter selects only firms for which the sum of AUM of the firm's funds that are reported in the database is close to the firm AUM. This filter removes firms for which firm AUM is not reported in the database and the firms that report to the database some but not all of their hedge funds. This filter ensures that firm returns and firm investment strategy, which are determined from the data on firm's funds, are valid. However, in some interesting subsamples, this filter leaves me with too few funds, so I report results without it. The second AUM-based filter selects only firms for which the database AUM is available and it is close to the value of domestic equity assets reported on form 13F. When this filter is applied, the difference between 13F returns and the database returns is primarily due to intra-quarter trading, trading costs, and fund fees. When the filter is not applied, the return difference is also due to other asset classes, leverage, and short selling.

The correlation between the database returns and 13F returns is above 55% for every strategy subsample except the fixed income strategy. When most firm's assets are accounted for by 13F assets, the return correlations are above 67% for all subsamples. The highest correlation, 97% is in the sample of long-only funds, however the sample is small. In the large sample of long-only and long-bias funds, the correlations are above 82%. In the complete sample of all strategies, the correlation is 67% when close to all assets of the firm are in 13F, and the correlation is 55% when the filter is not applied. Griffin and Xu (2009) also evaluate the correlation of 13F-based return and total database returns. They find a mean correlation of 0.55 and a median correlation of 0.64 in their sample. These findings are consistent with the findings discussed here.

The intercept is significant in some subsamples indicating a bias when 13F returns are used as an approximation for total returns. When most firm's assets are in 13F, the bias is significant only in the sample of long-only and long-bias funds.

The bias is 25 basis points per month in magnitude and its negative sign implies that scaled 13F returns overestimate total fund returns. The bias could be due to the funds destroying alpha with their unobserved actions, but a more likely explanation is fund fees and trading costs. The bias remains significant when market returns are also included in the regression.

When the sample is not restricted to the firms with most assets in 13F, the complete sample of all strategies and a number of subsamples have significant positive intercept. The significance is not influenced by inclusion of market returns in the regression. For the sample of all strategies the magnitude of the intercept is 24 basis points per month and it is highly statistically significant with t-statistic of 5.31. This bias can be interpreted as evidence that hedge funds create additional alpha beyond what is observed in their 13F quarterly holdings, by trading in other asset classes, short selling, and leverage. The bias is particularly high and significant in the samples of fixed income and macro funds, and it is high in magnitude in the sample of emerging market funds but only marginally significant. However, in these samples, additional risk control factors or benchmarks are necessary to make a conclusion about alpha creation through unobserved actions.

The sample used in this study is most closely represented by the sample of all strategies without the filter on 13F assets being close to the total firm assets. In this sample the return correlation is 55%. The coefficient on the 13F return is significantly below 1, indicating that total hedge fund returns are less volatile. The intercept is positive and highly significant, and it is 24 basis points per month in magnitude. The direction of the bias indicates that hedge funds create additional alpha by their unobserved actions.

1.9 Conclusion

In this paper I demonstrate that there are skilled investors able to earn significant factor-adjusted profits. Existence of large performance fees and slow flows in the hedge fund industry make hedge fund managers more likely to persistently outperform than other types of investment advisors. Further, since having large holdings in a portfolio come at the costs of less diversification and more price impact, large holdings must be held only if the manager estimates them to have higher expected returns. Therefore, I study the skill of managing hedge funds by evaluating their average performance, performance persistence, and their best ideas, and find the strongest evidence of skill in best ideas of best funds.

I evaluate performance using 13F holdings-based returns on the domestic equity part of the hedge fund portfolio. This allows me to study the return on the part of the portfolio which we understand relatively well and know how to adjust for risk. I construct my own sample of hedge funds that is comprehensive in its coverage of domestic equity hedge funds, is one of the longest samples used in hedge fund literature, and is free of palpable survivorship and self-reporting biases.

I find economically and statistically significant performance of the average fund and performance persistence. But the strongest evidence of hedge fund skill is found in strong performance of best ideas of best managers. The results are robust to alternative testing methodologies, hold in subsamples, and hold in an alternative sample. Given the size and the quality of the hedge fund sample as well as well-understood risk-adjustment and testing methodology, this paper provides a strong evidence on the existence of their investment skill.

Figure 1.1: Sample Sizes in Related Studies

This figure plots the hedge fund sample size by year, comparing our sample to the studies that also use 13F filings of hedge fund managers. Griffin and Xu obtain hedge fund names from several databases, primarily from AltVest, Mar, Nelsons Directory, and TASS, and match these names to 13F filings. Ben-David et al (2011, 2012) use a proprietary classification used internally by Thomson Financial that identifies hedge fund firms among 13F filers.

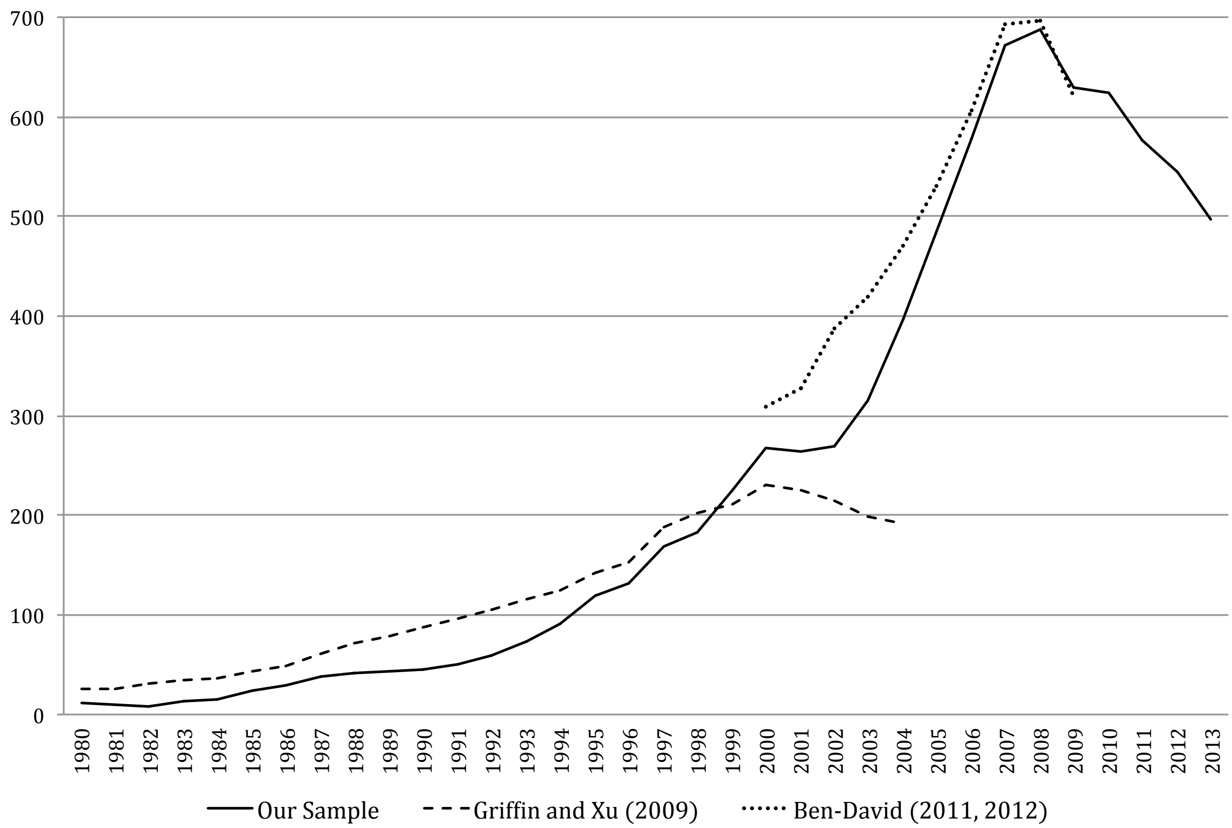

Table 1.1: Sample Size

This table reports size of the hedge fund firm sample, important subsamples, and the number of portfolio holdings. “Fund” refers to a hedge fund firm. After Filters subsample includes the funds that hold at least 5 stocks, have at least $10 million in 13F assets under management, and 50% of assets reported in 13F are domestic equity. Large holdings are defined as holdings with portfolio weights greater than 5%.

	Number of funds		Average number of funds per quarter			Average number of stocks per quarter per fund		Average number of distinct large holdings of all funds per quarter	
Year	Initial sample	After filters	Have holdings data in prior four quarters	Have large holdings	Have holdings data in prior four quarters and have large holdings	All holdings	Large holdings	All funds	Funds with holdings data in prior four quarters
1980	11	11	-	6	-	86	2.7	16	-
1981	9	9	6	3	3	103	2	6	5
1982	8	8	5	5	3	95	3.1	14	6
1983	14	14	7	7	5	118	3.4	22	11
1984	16	16	9	10	5	102	3.4	27	18
1985	24	22	12	12	7	102	4.2	40	25
1986	29	28	16	17	11	97	4.3	58	35
1987	38	37	21	23	14	91	4.8	90	58
1988	42	41	21	23	15	87	4.5	80	59
1989	43	42	23	28	17	81	3.9	79	48
1990	46	45	23	31	19	70	4.1	97	62
1991	50	49	26	34	21	74	3.9	95	64
1992	59	58	30	38	22	82	3.7	111	64
1993	73	71	39	45	30	83	3.9	139	87
1994	91	88	44	61	35	77	4.4	200	111
1995	119	115	60	77	50	80	4.2	244	169
1996	132	128	67	85	56	77	4.3	278	195
1997	168	166	76	105	63	88	4.4	347	226
1998	182	179	97	129	81	91	4.6	423	287
1999	225	217	111	148	97	89	4.3	421	310
2000	268	263	145	182	123	93	4.3	476	341
2001	264	258	175	184	141	100	4.7	503	417
2002	270	257	165	190	133	99	4.6	543	409
2003	315	296	181	171	135	118	4.5	493	392
2004	397	378	195	245	150	116	4.4	618	409
2005	485	466	265	315	209	113	4.9	810	594
2006	578	548	335	381	274	115	5.2	1007	755
2007	672	636	395	444	330	115	5.4	1156	920
2008	688	645	415	474	361	95	5.7	1241	1054
2009	629	567	371	402	314	96	5.4	1031	884
2010	624	565	363	386	299	111	5.3	963	807
2011	577	542	400	430	337	104	5.5	1040	890
2012	545	500	417	400	359	102	5.6	991	933
2013	497	458	377	361	319	112	5.6	940	872
Total distinct	1154	1116							

Table 1.2: Performance of All Hedge Funds: Portfolio Test

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the strategy portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The strategy portfolio invests equally in all sample hedge funds and is rebalanced monthly. The strategy portfolio return is calculated as the equal-weighted average of the returns of all funds. Fund return in a given month is approximated by return on the portfolio reported in the most recent 13F form. Here we do not allow for the 45-day gap between a quarter-end the public availability of the 13F form. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is Apr 1980 – Dec 2013.

	(1)	(2)	(3)
α	14.11	14.89	11.86
	(1.58)	(2.35)	(1.90)
β_{MKT}	1.13	1.06	1.07
	(49.84)	(55.43)	(61.04)
β_{SMB}		0.38	0.38
		(14.66)	(14.85)
β_{HML}		−0.01	−0.01
		(−0.28)	(−0.30)
β_{MOM}		−0.04	−0.04
		(−2.38)	(−2.39)
β_{LIQ}			0.06
			(2.47)
R^2	92	96	97
Obs	405	405	405

Table 1.3: Performance of Stocks Owned by Hedge Funds: Fama-MacBeth Test

This table reports $\lambda^{Ownership}$ coefficient estimates of the following Fama-MacBeth regression of monthly stock returns:

$$r_{i,t} = \alpha_t + \lambda_t^{Ownership} Ownership_{i,t} + \lambda_t^{MKT} \beta_{i,t}^{MKT} + \lambda_t^{SMB} \beta_{i,t}^{SMB} + \lambda_t^{HML} \beta_{i,t}^{HML} + \lambda_t^{MOM} \beta_{i,t}^{MOM} + \lambda_t^{LIQ} \beta_{i,t}^{LIQ} + \epsilon_{i,t}$$

$$\lambda^{Ownership} = \frac{1}{T} \sum_{t=1}^{T} \lambda_t^{Ownership}$$

Here $r_{i,t}$ is return of stock i in month t. Betas are estimated in time-series regressions over rolling 24-month windows. Variable $Ownership_{i,t}$ measures hedge fund industry ownership of the stock, i.e. aggregate ownership by all hedge funds. In specification (1), $Ownership_{i,t}$ is an indicator variable that is equal to one if the stock is held by at least one hedge fund, and zero otherwise. In specification (2), $Ownership_{i,t}$ is equal to the fraction of hedge funds owning the stock in percentage points; 1% increase in the fraction of funds holdings the stock corresponds to the extra return shown in the table in basis points per month. In specification (3), $Ownership_{i,t}$ is equal to stock weight in the hedge fund industry aggregate long domestic equity portfolio, and is calculated as the sum of the dollar positions in this stock across all hedge funds divided by the sum of total long domestic equity assets of all hedge funds multiplied by 100%; 1% weight of the stock in the industry portfolio corresponds to the extra return shown in the table in basis points per month. The table shows in columns various regression specifications that include one or more $Ownership_{i,t}$ variables. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Coefficients are reported in basis points per month. The sample period of strategy returns is Apr 1980 – Dec 2013.

Ownership Measure	(1)	(2)	(3)
HF-industry ownership indicator	18		
	(2.0)		
Fraction of HF holding the stock		2.4	
		(1.5)	
HF-industry weight			2.4
			(0.0)

Table 1.4: Performance Persistence: Portfolio Test

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the calendar-time portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The calendar-time portfolio holds complete portfolios of the best funds. The portfolio return is calculated as the equal-weighted average of the returns of the best funds. A hedge fund is considered a best fund if it is above a certain quantile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. Fund return in a given month is approximated by return on the portfolio reported in the most recent 13F form. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is either Apr 1981 – Dec 2013 or Apr 1985 – Dec 2013.

	1981–2013						1985–2013					
	Top half			Bottom half			Top half			Top quartile		
α	33.23	25.65	21.95	−4.91	4.49	2.63	33.46	27.69	24.29	44.87	32.54	28.42
	(3.13)	(2.97)	(2.49)	(−0.50)	(0.73)	(0.44)	(2.92)	(3.25)	(2.75)	(3.21)	(2.97)	(2.45)
β_{MKT}	1.10	1.04	1.05	1.16	1.09	1.09	1.11	1.05	1.05	1.07	1.04	1.04
	(37.40)	(40.22)	(41.25)	(39.40)	(54.29)	(60.00)	(35.18)	(36.92)	(38.34)	(25.48)	(28.73)	(29.26)
β_{SMB}		0.45	0.45		0.31	0.31		0.46	0.47		0.46	0.47
		(8.72)	(8.89)		(4.02)	(4.05)		(9.64)	(9.74)		(7.19)	(7.41)
β_{HML}		0.02	0.02		0.02	0.02		0.01	0.02		0.07	0.07
		(0.35)	(0.37)		(0.32)	(0.34)		(0.25)	(0.42)		(0.94)	(1.10)
β_{MOM}		0.08	0.08		−0.16	−0.16		0.08	0.07		0.14	0.14
		(1.80)	(1.73)		(−4.66)	(−4.75)		(1.73)	(1.66)		(2.66)	(2.56)
β_{LIQ}			0.07			0.04			0.08			0.09
			(2.67)			(1.22)			(2.56)			(2.40)
R^2	87	94	94	90	94	94	87	94	94	81	90	90
Obs	393	393	393	393	393	393	345	345	345	345	345	345

Table 1.5: Performance Persistence: Long-Short Portfolio Test

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the calendar-time portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The calendar-time portfolio is a long-short portfolio. The long part of the portfolio holds 13F portfolios of the best funds with equal weight given to each fund. The short part of the portfolio holds 13F portfolios of all funds with equal weight given to each fund. The calendar-time portfolio return is calculated monthly as the return of the long portfolio minus the return of the short portfolio. A hedge fund is considered a best fund if it is above a certain quantile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is either Apr 1981 – Dec 2013 or Apr 1985 – Dec 2013.

	Top half 1981–2013			Top quartile 1985–2013		
α	20.90	11.19	10.34	31.16	15.06	13.91
	(4.00)	(2.47)	(2.12)	(3.11)	(1.87)	(1.59)
β_{MKT}	−0.03	−0.02	−0.02	−0.07	−0.03	−0.03
	(−1.70)	(−1.26)	(−1.19)	(−1.86)	(−1.13)	(−1.10)
β_{SMB}		0.06	0.07		0.07	0.07
		(1.08)	(1.10)		(0.97)	(1.00)
β_{HML}		0.02	0.02		0.06	0.06
		(0.43)	(0.43)		(0.91)	(0.94)
β_{MOM}		0.12	0.12		0.19	0.19
		(3.56)	(3.53)		(4.30)	(4.25)
β_{LIQ}			0.02			0.03
			(1.17)			(0.96)
R^2	2	30	30	3	32	32
Obs	393	393	393	345	345	345

Table 1.6: Performance of Stocks Owned by Best Hedge Funds: Fama-MacBeth Test

This table reports $\lambda^{Ownership}$ coefficient estimates of the following Fama-MacBeth regression of monthly stock returns:

$$r_{i,t} = \alpha_t + \lambda_t^{Ownership} Ownership_{i,t} + \lambda_t^{MKT} \beta_{i,t}^{MKT} + \lambda_t^{SMB} \beta_{i,t}^{SMB} + \lambda_t^{HML} \beta_{i,t}^{HML} + \lambda_t^{MOM} \beta_{i,t}^{MOM} + \lambda_t^{LIQ} \beta_{i,t}^{LIQ} + \epsilon_{i,t}$$

$$\lambda^{Ownership} = \frac{1}{T} \sum_{t=1}^{T} \lambda_t^{Ownership}$$

Here $r_{i,t}$ is return of stock i in month t. Betas are estimated in time-series regressions over rolling 24-month windows.Variable $Ownership_{i,t}$ measures hedge fund ownership of the stock. The table shows in columns various regression specifications that include one or more $Ownership_{i,t}$ variables. In specification (1), $Ownership_{i,t}$ is an indicator variable that is equal to one if the stock is held by at least one best fund, and zero otherwise. In specification (2), $Ownership_{i,t}$ is equal to the fraction of best hedge funds owning the stock in percentage points; 1% increase in the fraction of best funds holdings the stock corresponds to the extra return shown in the table in basis points per month. In specification (3), $Ownership_{i,t}$ is equal to the stock's weight in the aggregate portfolio of all best funds, and is calculated as the sum of the dollar positions in this stock across all best funds divided by the sum of total 13F assets of all best funds; 1% weight increase of the stock in the best funds portfolio corresponds to the extra return shown in the table in basis points per month. A hedge fund is considered a best fund if it is above a certain quantile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio of past returns. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Coefficients are reported in basis points per month. The sample period of strategy returns is Apr 1981 – Dec 2013.

Ownership Measure	Top Half of Past Performance 1981–2013			Top Quartile of Past Performance 1985–2013				
Best fund indicator	25			39			34	39
	(2.9)			(4.1)			(4.2)	(4.3)
Fraction of best funds holding the sock, %		2.8			3.5		0.6	
		(2.0)			(2.5)		(0.5)	
Weight in aggregate portfolio of all best funds, %			14			31		-3.4
			(0.3)			(1.0)		(-0.1)

Table 1.7: Best Ideas of All Funds: Calendar-Time Portfolio Tests

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the strategy portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The strategy portfolio holds the best ideas of all sample funds. The best ideas of a manager are stocks that have weights greater than 5% in the manager's 13F portfolio. In the strategy portfolio each best idea has weight proportional to the number of managers holding the stock as their best idea. Alternatively, the strategy portfolio holds all stocks of all funds except their best ideas. In the alternative strategy portfolio each stock has weight proportional to the number of managers holding the stock. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is Apr 1980 – Dec 2013.

	Best Ideas			Other Holdings		
α	20.23	19.75	14.90	9.84	15.84	13.33
	(1.85)	(2.21)	(1.66)	(0.91)	(2.72)	(2.47)
β_{MKT}	1.08	1.03	1.03	1.23	1.13	1.13
	(29.30)	(32.20)	(35.02)	(45.52)	(75.84)	(80.73)
β_{SMB}		0.34	0.34		0.52	0.53
		(10.00)	(10.17)		(17.00)	(17.30)
β_{HML}		0.02	0.02		−0.01	−0.01
		(0.62)	(0.81)		(−0.47)	(−0.50)
β_{MOM}		−0.04	−0.04		−0.13	−0.13
		(−1.82)	(−1.89)		(−5.60)	(−5.62)
β_{LIQ}			0.09			0.05
			(3.48)			(2.57)
R^2	87	91	91	90	97	98
Obs	405	405	405	405	405	405

Table 1.8: Best Ideas of Best Funds: Portfolio Test

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the calendar-time portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The calendar-time portfolio holds the best ideas of the best funds. The calendar-time portfolio return is calculated as an equal-weighted average of returns of best ideas of best funds. Best ideas are defined as stocks that have weight of greater than 5% in most recent 13F portfolio of a fund. A hedge fund is considered a best fund if it is above a certain quantile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. Best ideas receive equal weights in the calendar-time portfolio and if a stock is among the best ideas of n funds then it receives n-times the weight. Column "Other holdings" refers holdings that are not best ideas but are held by best funds that have best ideas. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is either Apr 1981 – Dec 2013 or Apr 1985 – Dec 2013.

	1985–2013												1981–2013		
	Top quartile			Top half			Bottom half			Other holdings			Top half		
α	68.14	57.68	52.60	46.96	40.10	35.06	−10.48	2.36	−0.17	36.50	34.89	30.97	45.85	34.48	26.84
	(4.21)	(3.74)	(3.23)	(3.55)	(3.33)	(2.78)	(−0.76)	(0.25)	(−0.02)	(2.35)	(3.23)	(2.87)	(3.67)	(2.84)	(2.08)
β_{MKT}	1.02	0.98	0.98	1.05	0.99	1.00	1.14	1.07	1.07	1.19	1.10	1.10	1.02	0.98	0.98
	(15.48)	(14.93)	(15.36)	(20.10)	(19.12)	(19.89)	(25.82)	(32.96)	(35.52)	(30.62)	(42.33)	(43.10)	(19.79)	(20.15)	(21.03)
β_{SMB}		0.42	0.43		0.47	0.47		0.28	0.28		0.62	0.62		0.43	0.44
		(5.85)	(6.10)		(6.63)	(6.67)		(3.22)	(3.29)		(12.37)	(12.75)		(5.48)	(5.61)
β_{HML}		0.03	0.04		0.00	0.01		0.05	0.05		0.06	0.06		0.04	0.04
		(0.34)	(0.47)		(0.08)	(0.27)		(0.64)	(0.78)		(0.99)	(1.23)		(0.71)	(0.75)
β_{MOM}		0.13	0.13		0.10	0.09		−0.20	−0.20		0.00	0.00		0.12	0.11
		(1.95)	(1.89)		(1.59)	(1.53)		(−5.20)	(−5.37)		(−0.08)	(−0.10)		(1.92)	(1.83)
β_{LIQ}			0.11			0.11			0.06			0.09			0.15
			(2.30)			(2.95)			(1.48)			(2.91)			(3.67)
R^2	71	78	79	79	87	88	86	90	90	84	94	94	74	81	82
Obs	345	345	345	345	345	345	345	345	345	345	345	345	393	393	393

Table 1.9: Best Ideas of Best Funds: Long-Short Portfolio Test

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the calendar-time portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The calendar-time portfolio is a long-short portfolio. The long part of the portfolio is the "best ideas of best funds" portfolio. The short part of the portfolio is one of the portfolios described below. The calendar-time portfolio return is calculated monthly as the return of the long portfolio minus the return of the short portfolio. The "best ideas of best funds" portfolio return is calculated as an equal-weighted average of returns of best ideas of best funds. Best ideas are defined as stocks that have weight of greater than 5% in most recent 13F portfolio of a fund. A hedge fund is considered a best fund if it is in the top quartile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. Best ideas receive equal weights in the calendar-time portfolio and if a stock is a best ideas of n mangers then it receives n-times the weight. The short portfolio is one of the following portfolios. The "Average fund" portfolio invests equally in the portfolios of all sample hedge fund managers and is rebalanced monthly; therefore the calendar-time portfolio return is calculated as an equal-weighted average of returns of all sample hedge fund portfolios. The "Best funds" portfolio invests equally in all best funds. The "Best funds having best ideas" invests in complete portfolios of best funds that have at least on best idea. The "Other holdings of best funds with best ideas" is a portfolio of stocks that are held by the best funds having best ideas but excludes the best ideas themselves. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is Apr 1985 – Dec 2013.

	Short portfolio											
	Average fund			Best funds			Best funds having best ideas			Other holdings of best funds having best ideas		
α	54.43	40.20	38.09	23.27	25.13	24.18	23.80	25.46	24.80	35.53	25.13	23.81
	(4.22)	(3.18)	(2.86)	(2.46)	(2.59)	(2.52)	(2.64)	(2.78)	(2.72)	(2.49)	(1.81)	(1.73)
β_{MKT}	−0.12	−0.09	−0.09	−0.05	−0.06	−0.06	−0.03	−0.03	−0.03	−0.16	−0.11	−0.11
	(−2.32)	(−1.65)	(−1.65)	(−1.49)	(−1.47)	(−1.48)	(−0.97)	(−1.13)	(−1.14)	(−3.89)	(−2.30)	(−2.32)
β_{SMB}		0.03	0.03		−0.04	−0.04		−0.02	−0.02		−0.19	−0.19
		(0.38)	(0.43)		(−1.34)	(−1.32)		(−0.87)	(−0.84)		(−4.40)	(−4.42)
β_{HML}		0.02	0.02		−0.04	−0.04		−0.06	−0.06		−0.03	−0.03
		(0.23)	(0.27)		(−1.30)	(−1.18)		(−2.16)	(−2.04)		(−0.90)	(−0.80)
β_{MOM}		0.19	0.19		−0.01	−0.01		0.01	0.01		0.16	0.16
		(3.03)	(2.99)		(−0.19)	(−0.20)		(0.29)	(0.28)		(4.43)	(4.39)
β_{LIQ}			0.05			0.02			0.01			0.03
			(1.16)			(1.03)			(0.85)			(0.91)
R^2	5	17	18	2	3	3	1	2	2	8	22	22
Obs	345	345	345	345	345	345	345	345	345	345	345	345

Table 1.10: Performance of Best Ideas of Best Funds: Fama-MacBeth Test

This table reports $\lambda^{Ownership}$ coefficient estimates of the following Fama-MacBeth regression of monthly stock returns:

$$r_{i,t} = \alpha_t + \lambda_t^{Ownership} Ownership_{i,t} + \lambda_t^{MKT} \beta_{i,t}^{MKT} + \lambda_t^{SMB} \beta_{i,t}^{SMB} + \lambda_t^{HML} \beta_{i,t}^{HML} + \lambda_t^{MOM} \beta_{i,t}^{MOM} + \lambda_t^{LIQ} \beta_{i,t}^{LIQ} + \epsilon_{i,t}$$

$$\lambda^{Ownership} = \frac{1}{T} \sum_{t=1}^{T} \lambda_t^{Ownership}$$

Here $r_{i,t}$ is return of stock i in month t. Betas are estimated in time-series regressions over rolling 24-month windows. The table shows in columns regression specifications (1)–(5) that include one or more $Ownership_{i,t}$ variables. Variable $Ownership_{i,t}$ measures hedge fund ownership of the stock. In specification "Best idea of best fund indicator", $Ownership_{i,t}$ is an indicator variable that is equal to one if the stock is the best idea of at least one best fund, and zero otherwise. In specification "Industry indicator", $Ownership_{i,t}$ is equal to one if the stock is held by at least one fund, and zero otherwise. In specification "Best fund indicator", $Ownership_{i,t}$ is an indicator variable that is equal to one if the stock is held by at least one best fund, and zero otherwise. In specification "Best idea indicator", $Ownership_{i,t}$ is equal to one if the stock is the best idea of at least one fund, and zero otherwise. Best ideas are defined as stocks that have weight of greater than 5% in a managers most recent 13F portfolio. A hedge fund is considered the best fund if it is in top quartile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio of past returns. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Coefficients are reported in basis points per month. The sample period of strategy returns is Apr 1985 – Dec 2013.

Ownership Measure	(1)	(2)	(3)	(4)	(5)
Best idea of	58	47	29	51	37
best fund indicator	(3.4)	(3.1)	(2.1)	(3.5)	(2.6)
Industry indicator		20			9.0
		(2.1)			(1.0)
Best fund indicator			38		32
			(4.1)		(3.7)
Best idea indicator				6.5	-10
				(0.6)	(-1.0)

Table 1.11: Performance of Mutual Funds: Calendar-Time Portfolio Tests

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the calendar-time portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The calendar-time portfolio is an equal weighted portfolio of one of the following: all funds, best funds, best ideas of all funds, or best ideas of best funds. In the specification "Best ideas of best funds: Long HF, short MF", the calendar-time portfolio is long best ideas of best hedge funds and is short best ideas of best mutual funds. In this specification the regression does not include the risk free return on the left side. Best ideas are defined as stocks that have weight of greater than 5% in a manager's most recent 13F. A fund is considered a best fund if it is in the top half of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is Apr 1985 – Dec 2013.

	All funds			Best funds (top quartile)			Best ideas of all funds			Best ideas of best funds			Best ideas of best funds: Long HF - Short MF		
α	4.58	2.68	3.04	36.05	19.11	17.89	5.27	7.91	11.88	41.06	24.75	26.65	28.79	36.07	29.16
	(0.85)	(0.68)	(0.72)	(3.54)	(2.43)	(2.08)	(0.73)	(1.26)	(1.83)	(3.45)	(2.45)	(2.42)	(1.71)	(2.51)	(2.03)
β_{MKT}	1.00	0.97	0.97	0.96	0.93	0.93	1.11	1.08	1.08	1.09	1.08	1.08	−0.05	−0.10	−0.09
	(83.29)	(93.67)	(90.37)	(29.57)	(27.71)	(27.29)	(44.61)	(65.35)	(70.98)	(21.07)	(25.00)	(25.37)	(−0.71)	(−1.85)	(−2.01)
β_{SMB}		0.20	0.20		0.38	0.38		0.01	0.00		0.13	0.13		0.28	0.29
		(7.10)	(7.05)		(7.06)	(7.12)		(0.23)	(0.10)		(2.36)	(2.30)		(5.10)	(5.35)
β_{HML}		0.01	0.01		0.05	0.05		−0.19	−0.19		−0.18	−0.18		0.17	0.18
		(0.22)	(0.21)		(0.84)	(0.83)		(−4.54)	(−4.70)		(−2.29)	(−2.31)		(2.19)	(2.34)
β_{MOM}		0.00	0.00		0.17	0.17		0.09	0.09		0.34	0.34		−0.19	−0.19
		(0.21)	(0.22)		(3.62)	(3.59)		(4.14)	(4.49)		(5.22)	(5.29)		(−4.90)	(−5.31)
β_{LIQ}			−0.01			0.02			−0.07			−0.04			0.16
			(−0.40)			(1.04)			(−3.55)			(−0.92)			(3.29)
R^2	96	98	98	84	92	92	92	94	95	75	85	86	1	17	21
Obs	405	405	405	405	405	405	405	405	405	405	405	405	345	345	345

Table 1.12: Implementable Strategies

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here we study implementable strategies and therefore we allow for the 45-day gap between the quarter-end and public availability of 13F form holdings. Best ideas are defined as stocks that have weight of greater than 5% in a manager's most recent 13F. A fund is considered a best fund if it is in the top quartile of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. The strategy portfolio is an equal weighted portfolio of one of the following: all funds, best funds, best ideas of all funds, or best ideas of best funds. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is Jun 1985 – Dec 2013.

	All funds			Best funds (top quartile)			Best ideas of all funds			Best ideas of best funds		
α	7.99	10.11	7.55	42.18	27.69	25.41	10.51	17.90	14.51	53.99	40.54	38.07
	(0.92)	(1.72)	(1.27)	(3.38)	(2.78)	(2.33)	(1.08)	(2.45)	(1.96)	(3.53)	(2.64)	(2.40)
β_{MKT}	1.14	1.08	1.08	1.09	1.06	1.06	1.16	1.09	1.09	1.11	1.08	1.08
	(48.71)	(53.33)	(58.50)	(30.26)	(38.20)	(37.52)	(33.87)	(40.92)	(44.09)	(18.36)	(21.10)	(21.10)
β_{SMB}		0.38	0.38		0.44	0.45		0.32	0.33		0.43	0.43
		(14.47)	(15.06)		(6.36)	(6.49)		(8.25)	(8.56)		(7.38)	(7.64)
β_{HML}		0.02	0.02		0.06	0.07		−0.01	0.00		0.05	0.05
		(0.42)	(0.72)		(0.88)	(0.97)		(−0.21)	(−0.02)		(0.66)	(0.74)
β_{MOM}		−0.04	−0.04		0.17	0.17		−0.10	−0.10		0.17	0.16
		(−2.55)	(−2.54)		(3.21)	(3.14)		(−6.08)	(−6.46)		(2.51)	(2.46)
β_{LIQ}			0.06			0.05			0.08			0.06
			(2.23)			(1.31)			(2.35)			(1.12)
R^2	92	97	97	81	90	90	91	94	95	75	82	82
Obs	343	343	343	343	343	343	343	343	343	343	343	343

Table 1.13: Robustness check: Subsamples 1985-1999 and 2000-2013

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the strategy portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The strategy portfolio is an equal weighted portfolio of one of the following: all funds, best funds, best ideas of all funds, or best ideas of best funds.Best ideas are defined as stocks that have weight of greater than 5% in a manager's most recent 13F. A fund is considered a best fund if it is in the top half of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis. Estimates of α are reported in basis points per month. The sample period of strategy returns is Apr 1985 – Dec 1999 in Panel A and Jan 2000 – Dec 2013 in Panel B.

	All funds			Best funds (top half)			Best ideas of all funds			Best ideas of best funds		
Panel A: 1985–1999												
α	−1.15	13.91	12.95	16.20	20.39	19.35	3.04	18.83	17.41	37.39	46.49	43.99
	(−0.08)	(1.58)	(1.47)	(1.11)	(2.01)	(1.91)	(0.19)	(1.73)	(1.58)	(1.86)	(2.73)	(2.59)
β_{MKT}	1.08	1.03	1.04	1.08	1.01	1.01	1.02	0.99	0.99	0.97	0.92	0.92
	(29.20)	(30.59)	(30.98)	(23.34)	(23.17)	(23.73)	(18.60)	(21.76)	(22.53)	(12.62)	(12.24)	(12.77)
β_{SMB}		0.43	0.45		0.41	0.43		0.37	0.40		0.39	0.44
		(11.91)	(12.41)		(8.18)	(8.19)		(8.02)	(8.71)		(4.46)	(5.15)
β_{HML}		−0.02	−0.01		−0.03	−0.03		−0.01	0.00		−0.03	−0.02
		(−0.47)	(−0.36)		(−0.56)	(−0.48)		(−0.27)	(−0.11)		(−0.41)	(−0.26)
β_{MOM}		−0.02	−0.01		0.11	0.11		−0.05	−0.04		0.05	0.05
		(−0.59)	(−0.50)		(2.52)	(2.50)		(−1.65)	(−1.46)		(0.73)	(0.77)
β_{LIQ}			0.05			0.05			0.07			0.12
			(3.49)			(2.00)			(2.27)			(2.60)
Panel B: 2000–2013												
α	33.92	22.10	15.73	54.19	32.97	27.17	34.33	26.27	18.90	63.33	43.63	37.90
	(2.99)	(2.68)	(2.09)	(4.22)	(3.28)	(2.57)	(3.11)	(2.53)	(1.97)	(4.83)	(3.20)	(2.58)
β_{MKT}	1.20	1.10	1.09	1.15	1.08	1.07	1.20	1.12	1.12	1.13	1.09	1.09
	(55.64)	(42.49)	(48.62)	(34.35)	(27.61)	(30.18)	(45.76)	(33.73)	(36.97)	(22.47)	(20.85)	(21.64)
β_{SMB}		0.36	0.35		0.49	0.48		0.27	0.26		0.46	0.45
		(10.72)	(11.15)		(8.35)	(7.37)		(6.94)	(7.77)		(7.03)	(6.16)
β_{HML}		0.01	0.02		0.03	0.04		−0.01	0.00		−0.02	−0.01
		(0.21)	(0.70)		(0.39)	(0.70)		(−0.21)	(0.05)		(−0.30)	(−0.17)
β_{MOM}		−0.05	−0.06		0.07	0.07		−0.03	−0.04		0.14	0.14
		(−2.95)	(−3.04)		(1.40)	(1.26)		(−1.64)	(−1.64)		(2.00)	(1.85)
β_{LIQ}			0.09			0.09			0.11			0.08
			(2.61)			(1.77)			(2.98)			(1.56)

Table 1.14: Robustness Tests: Alternative Sample by Morningstar

This table reports coefficients of the following time-series regression of monthly returns:

$$r_t - r_{f,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{LIQ} LIQ_t + \epsilon_t$$

Here r_t is the monthly return of the calendar-time portfolio that is described below. LIQ is the traded liquidity factor of Pastor and Stambaugh (2003). The calendar-time portfolio is an equal weighted portfolio of one of the following: all funds, best funds, best ideas of all funds, or best ideas of best funds. Best ideas are defined as stocks that have weight of greater than 5% in the portfolio of a fund. A fund is considered a best fund if it is in the top half of past performance. Past performance is measured by the rolling twelve-month Sharpe ratio. T-statistics are Newey-West adjusted with 12 lags and are reported in parenthesis.Estimates of α are reported in basis points per month. The sample period of strategy returns is Jan 1994 – Dec 2013.

	All funds			Best funds (top half)			Best ideas of all funds			Best ideas of best funds		
α	11.02	8.34	5.15	32.24	22.19	17.80	10.27	8.77	5.08	47.14	35.53	30.06
	(1.16)	(1.39)	(0.86)	(2.56)	(2.61)	(2.02)	(0.94)	(0.98)	(0.55)	(2.91)	(2.71)	(2.12)
β_{MKT}	1.13	1.08	1.07	1.10	1.07	1.07	1.15	1.10	1.10	1.09	1.09	1.08
	(68.61)	(67.38)	(77.83)	(37.34)	(49.94)	(55.86)	(47.85)	(42.38)	(44.40)	(23.13)	(28.65)	(29.15)
β_{SMB}		0.27	0.27		0.34	0.34		0.24	0.24		0.25	0.25
		(10.86)	(11.47)		(10.00)	(9.96)		(7.67)	(7.86)		(7.33)	(7.31)
β_{HML}		0.04	0.05		0.05	0.06		−0.03	−0.02		−0.01	0.00
		(0.97)	(1.47)		(0.89)	(1.14)		(−0.66)	(−0.67)		(−0.12)	(0.00)
β_{MOM}		−0.02	−0.02		0.07	0.07		0.00	0.00		0.14	0.14
		(−1.35)	(−1.36)		(1.74)	(1.62)		(−0.02)	(−0.09)		(2.32)	(2.18)
β_{LIQ}			0.06			0.08			0.07			0.10
			(2.13)			(2.52)			(2.13)			(2.27)
R^2	95	98	98	90	96	96	93	96	96	85	90	90
Obs	240	240	240	240	240	240	240	240	240	240	240	240

Table 1.15: Volume Announcement Effect of 13F Filings

The table presents results of the following pooled regression of daily returns:

$$\text{Log}[1 + \text{Vol}_{s,t}] = \sum_{\ell=-5}^{5} \beta_\ell \text{Disclosure}_{s,t+\ell} + a + \epsilon_{s,t}$$

where $\text{Vol}_{s,t}$ is the number of shares of stock s traded on the exchange on day t. $\text{Disclosure}_{s,t}$ is one of the following measures of information about stock s aggregated over all 13F filings made on date t: *All Funds Disclosing All Changes* is the number of funds reporting changes in their stock s shares held; *Best Funds Disclosing All Changes* is the number of fund that are disclosing shares held changes and that are in the top quartile of past one year performance; *Best Funds Disclosing Changes in Large Holdings* is the number of the top quartile funds that are disclosing stock s shares held changes and that have stock s portfolio weights greater than 5%; *Best Funds Disclosing Large Changes* is the number of the top quartile funds disclosing portfolio weight changes that are greater than 5% in magnitude. The sample period is Apr 1999 - Dec 2014. All reported coefficients are scaled up by 100.

Lags of Independent Variable	Independent Variable Type									
	All Funds Disclosing All Changes		All Funds Disclosing All Changes		Best Funds Disclosing All Changes		Best Funds Disclosing Changes in Large Holdings		Best Funds Disclosing Large Changes	
lag 5	−0.19	(−0.90)	−0.18	(−1.27)	−0.78	(−1.84)	−1.27	(−1.08)	−1.36	(−0.78)
lag 4	0.07	(0.35)	−0.04	(−0.30)	−0.62	(−1.19)	−0.23	(−0.23)	0.03	(0.02)
lag 3	0.17	(1.04)	0.12	(1.05)	0.17	(0.33)	0.92	(0.94)	0.89	(0.72)
lag 2	0.04	(0.21)	0.03	(0.26)	−0.08	(−0.16)	0.38	(0.36)	−0.34	(−0.25)
lag 1	−0.02	(−0.19)	0.04	(0.42)	0.04	(0.10)	0.00	(0.00)	−0.59	(−0.49)
lag 0	−0.21	(−2.19)**	−0.15	(−1.96)**	−0.69	(−2.27)**	−1.47	(−2.33)**	−1.96	(−2.02)**
lead 1	−0.09	(−0.60)	−0.13	(−1.35)	−0.71	(−2.60)**	−1.56	(−2.21)**	−2.34	(−2.20)**
lead 2	0.14	(0.69)	0.01	(0.08)	−0.17	(−0.34)	−0.17	(−0.17)	−0.14	(−0.13)
lead 3	0.42	(1.80)	0.24	(1.62)	0.64	(1.04)	0.84	(0.72)	0.56	(0.44)
lead 4	0.44	(1.70)	0.25	(1.65)	1.04	(1.67)	1.72	(1.46)	1.37	(1.00)
lead 5	0.78	(2.78)**	0.50	(3.07)**	1.80	(2.64)**	3.23	(2.63)**	2.25	(1.58)
Nobs	28,109,655		28,109,655		28,109,655		28,109,655		28,109,655	
Date Clustering	Yes		Yes		Yes		Yes		Yes	
Stock Clustering	Yes		No		No		No		No	
Stock-quarter FE	Yes		Yes		Yes		Yes		Yes	
Date FE	Yes		Yes		Yes		Yes		Yes	

Table 1.16: Return Announcement Effect of 13F Filings

The table presents results of the following pooled regression of daily returns:

$$\hat{r}_{s,t} = \sum_{\ell=-5}^{5} \beta_\ell \text{Disclosure}_{s,t+\ell} + a + \epsilon_{s,t}$$

where $\hat{r}_{s,t}$ is return of stock s on day t adjusted for the equal-weighted DGTW benchmark. Disclosure$_{s,t}$ is one of the following measures of information about stock s aggregated over all 13F filings made on date t: $Buyer\text{-}SellerRatio_{s,t}$ is the number of funds disclosing increases in shares held, minus the number of funds disclosing decreases in shares held, divided by the square root of the sum of the two; $Agg\ Weight\ Change_{s,t}$ is the stock weight change in the aggregate portfolio of all funds; $Sum\ Weight\ Change_{s,t}$ is the sum of fund portfolio weight changes; $Stake\ Change_{s,t}$ is the sum of shares-held changes divided by the shares outstanding; $Holders_{s,t}$ is the number of funds disclosing holdings of the stock; $Buyers_{s,t}$ is the number of funds disclosing increases in shares held. *Panels A-D* report results when disclosure measures account only for the following subsamples of disclosures: all disclosures in *Panel A*; disclosures by the funds in the top quartile of past year performance in *Panel B*; disclosures of portfolio weights greater than 5% by the top funds in *Panel C*; disclosures of portfolio weight changes greater than 5% in magnitude by the top funds in *Panel D*. Driscoll-Kraay spatial correlation robust t-statistics are reported in parentheses; they account for arbitrary correlation between any two errors within 22 days of each other and assume zero correlations for more distant errors. The sample period is Apr 1999 - Dec 2014 and there are 16,765,335 stock-day observations. All reported coefficients are scaled up by 100.

Panel A: Disclosure by All Funds

Lags of Independent Variable	Independent Variable Type							
	Buyer-Seller Ratio		Agg Weight Change		Sum Weight Change		Stake Change	
lag 5	0.000	(0.04)	−40.62	(−0.80)	−0.094	(−0.76)	0.399	(0.91)
lag 4	0.008	(1.61)	80.06	(1.45)	0.205	(2.34)**	0.745	(1.52)
lag 3	0.000	(0.11)	34.81	(0.86)	0.076	(0.74)	0.632	(1.72)
lag 2	0.010	(2.13)**	38.53	(1.16)	0.013	(0.20)	0.905	(2.16)**
lag 1	0.007	(1.73)	19.39	(0.60)	0.178	(1.74)	1.504	(3.67)**
lag 0	0.005	(1.18)	23.37	(0.65)	0.113	(1.39)	0.838	(1.78)
lead 1	0.001	(0.13)	17.94	(0.41)	0.031	(0.28)	0.067	(0.13)
lead 2	0.012	(2.61)**	60.88	(1.30)	0.028	(0.28)	0.104	(0.17)
lead 3	0.008	(1.98)**	44.02	(1.09)	0.130	(1.28)	0.329	(0.81)
lead 4	0.008	(1.83)	62.28	(1.75)	0.195	(1.80)	0.527	(1.30)
lead 5	0.001	(0.14)	−30.35	(−0.57)	−0.113	(−1.21)	0.137	(0.32)

Panel B: Disclosure by Best Funds

Lags of Independent Variable	Independent Variable Type							
	Buyer-Seller Ratio		Agg Weight Change		Sum Weight Change		Stake Change	
lag 5	0.004	(0.77)	4.79	(0.07)	−0.265	(−0.85)	1.934	(2.86)**
lag 4	0.009	(1.41)	115.67	(1.35)	0.219	(1.19)	1.316	(1.59)
lag 3	0.000	(0.08)	113.49	(1.82)	0.010	(0.04)	0.651	(0.80)
lag 2	0.007	(1.20)	45.08	(0.70)	0.083	(0.40)	0.992	(1.62)
lag 1	0.012	(2.06)**	32.44	(0.74)	0.207	(1.04)	1.546	(1.84)
lag 0	0.010	(1.63)	35.92	(0.55)	0.562	(3.12)**	1.521	(1.40)
lead 1	−0.001	(−0.19)	67.08	(1.30)	0.375	(1.87)	0.553	(0.80)
lead 2	0.010	(1.37)	13.62	(0.18)	−0.058	(−0.27)	0.357	(0.42)
lead 3	0.002	(0.23)	−88.22	(−1.70)	−0.013	(−0.06)	0.934	(0.98)
lead 4	0.011	(1.59)	91.34	(1.05)	0.344	(1.38)	0.312	(0.28)
lead 5	0.009	(1.41)	67.57	(0.59)	−0.077	(−0.33)	0.629	(0.66)

Table 1.16, cont.

Panel C: Disclosure of Best Ideas by Best Funds

Lags of Independent Variable	Independent Variable Type											
	Holders		Buyers		Buyer-Seller Ratio		Agg Weigh Change		Sum Weight Change		Stake Change	
lag 5	0.023	(1.44)	0.002	(0.13)	−0.028	(−1.32)	−39.74	(−0.50)	−0.290	(−1.14)	1.658	(1.65)
lag 4	0.018	(1.19)	0.029	(1.62)	0.028	(1.62)	198.27	(1.05)	0.274	(0.88)	4.157	(2.45)**
lag 3	−0.011	(−0.78)	−0.025	(−1.26)	−0.025	(−1.18)	51.76	(0.56)	−0.055	(−0.18)	0.020	(0.01)
lag 2	0.020	(1.11)	0.024	(1.30)	0.010	(0.58)	42.26	(0.30)	0.061	(0.21)	0.621	(0.57)
lag 1	0.013	(0.78)	0.011	(0.55)	−0.004	(−0.20)	7.30	(0.09)	0.250	(1.01)	−0.894	(−0.87)
lag 0	0.014	(0.84)	0.007	(0.33)	−0.016	(−0.64)	43.64	(0.49)	0.627	(1.95)	0.620	(0.40)
lead 1	0.042	(2.43)**	0.039	(1.95)	−0.002	(−0.09)	−9.20	(−0.08)	0.425	(1.26)	1.430	(1.00)
lead 2	0.003	(0.14)	0.013	(0.48)	0.021	(0.98)	−11.89	(−0.13)	−0.037	(−0.11)	0.827	(0.51)
lead 3	−0.016	(−0.81)	−0.026	(−1.02)	−0.019	(−0.89)	−118.43	(−1.61)	−0.484	(−1.25)	−0.795	(−0.37)
lead 4	0.024	(1.29)	0.030	(1.23)	0.023	(1.18)	90.42	(1.10)	0.619	(1.82)	−0.405	(−0.23)
lead 5	−0.007	(−0.31)	−0.005	(−0.19)	−0.004	(−0.23)	13.35	(0.10)	−0.246	(−0.86)	−1.485	(−0.91)

Panel D: Disclosure of Large Weight Changes by Best Funds

Lags of Independent Variable	Independent Variable Type							
	Buyer-Seller Ratio		Agg Weight Change		Sum Weight Change		Stake Change	
lag 5	0.000	(0.01)	70.65	(0.69)	−0.160	(−0.47)	−0.541	(−0.39)
lag 4	0.007	(0.23)	−33.59	(−0.42)	−0.086	(−0.34)	2.995	(2.01)**
lag 3	−0.018	(−0.78)	−2.77	(−0.04)	−0.191	(−0.79)	1.106	(0.79)
lag 2	0.006	(0.24)	174.75	(1.54)	0.029	(0.12)	1.683	(1.74)
lag 1	0.003	(0.11)	−20.41	(−0.34)	0.194	(0.83)	−0.505	(−0.42)
lag 0	0.014	(0.60)	50.65	(0.74)	0.343	(1.75)	1.415	(0.99)
lead 1	0.071	(2.70)**	141.50	(2.31)**	0.408	(1.86)	2.866	(1.87)
lead 2	0.014	(0.49)	−28.71	(−0.39)	−0.087	(−0.38)	1.183	(0.81)
lead 3	−0.021	(−0.77)	−100.06	(−1.32)	−0.256	(−1.08)	0.562	(0.31)
lead 4	0.054	(1.81)	48.27	(0.59)	0.478	(1.78)	−1.040	(−0.78)
lead 5	0.004	(0.15)	58.51	(0.54)	0.040	(0.15)	1.159	(1.18)

Table 1.17: Comparison of 13F Holdings-Based Returns with Total Returns

The table presents results of the following pooled regression:

$$r_{i,t} = br^{13F}_{i,t} + a + \beta R^m_t + \epsilon_{i,t}$$

where $r_{i,t}$ is the total return of hedge fund firm i in month t; $r^{13F}_{i,t}$ is the return on 13F holdings of the firm; R^m_t is the market return. The total firm return is calculated as the value-weighted average of the returns of the firm's hedge funds that report to BarclayHedge database. The database returns are reported net of fees. $Corr$ is the correlation of the total return and the 13F return. In the *second column*, Yes indicates the subsample where the sum of reported AUM of the firm's funds in the range of $0.75 - 1.25$ of the firm's AUM; Yes*indicates the subsample where the range is $0.5 - 1.5$; and No indicates that no such restriction has been applied and that observations with missing firm AUM are included. In the *third column*, *Yes* indicates the subsample where 13F assets value is in the range of $0.75 - 1.25$ of the firm's AUM; *No* indicates that no such restriction has been applied and that observations with missing firm AUM are included. N is the number of firm-month observations in the subsample. The sample period is Apr 1980 - Dec 2014. The intercept is displayed in percent per month. T-statistics are in parentheses to the right of the estimates.

Strategy	Only Firms With Reporting Funds AUM Close To Total AUM	Only Firms With 13F Assets Close To Total AUM		Regression without Market				Regression with Market			
			N	a	b	R^2	Corr	a	β	b	R^2
All Strategies	Yes	Yes	1220	−0.02 (−0.20)	0.45 (31.5)	0.45	0.67	−0.02 (−0.25)	−0.16 (−4.58)	0.53 (22.6)	0.46
	Yes	No	4814	0.24 (5.31)	0.30 (45.3)	0.30	0.55	0.24 (5.28)	−0.03 (−1.90)	0.31 (29.3)	0.30
Equity, Event Driven, Sector, no Emerging	Yes	Yes	1075	−0.06 (−0.62)	0.48 (32.1)	0.49	0.70	−0.07 (−0.66)	−0.15 (−4.01)	0.55 (22.5)	0.50
	Yes	No	3567	0.15 (2.81)	0.36 (47.2)	0.38	0.62	0.13 (2.54)	−0.09 (−4.70)	0.41 (32.0)	0.39
Equity, no Event Driven, no Sector, no Emerging	Yes	Yes	759	0.00 (0.00)	0.45 (25.5)	0.46	0.68	0.00 (0.02)	−0.18 (−3.74)	0.56 (17.2)	0.47
	Yes	No	2372	0.17 (2.59)	0.37 (39.4)	0.40	0.63	0.15 (2.41)	−0.07 (−3.00)	0.42 (24.5)	0.40
Long Only and Long Bias	Yes	Yes	454	−0.25 (−2.12)	0.65 (35.0)	0.73	0.85	−0.24 (−2.11)	−0.03 (−0.50)	0.66 (18.9)	0.73
	Yes	No	1024	−0.05 (−0.66)	0.58 (46.3)	0.68	0.82	−0.06 (−0.70)	−0.06 (−1.93)	0.62 (27.8)	0.68
Long Only	Yes*	Yes	28	−0.06 (−0.37)	0.60 (20.2)	0.94	0.97	−0.01 (−0.04)	−0.05 (−0.75)	0.61 (17.3)	0.94
	Yes*	No	32	0.02 (0.11)	0.59 (20.8)	0.93	0.97	0.05 (0.35)	−0.04 (−0.73)	0.60 (17.7)	0.94
	No	Yes	103	−0.19 (−2.14)	0.68 (45.0)	0.95	0.98	−0.19 (−2.12)	0.06 (2.28)	0.64 (29.5)	0.95
	No	No	223	−0.06 (−0.40)	0.49 (21.6)	0.68	0.82	−0.06 (−0.38)	0.04 (0.88)	0.47 (13.8)	0.68
Sector	Yes	Yes	247	−0.22 (−0.84)	0.49 (15.5)	0.49	0.70	−0.23 (−0.89)	−0.15 (−1.98)	0.56 (12.2)	0.50
	Yes	No	650	0.02 (0.12)	0.36 (18.1)	0.34	0.58	−0.03 (−0.20)	−0.27 (−5.72)	0.49 (16.4)	0.37
Event Driven	Yes	Yes	69	−0.15 (−0.73)	0.64 (18.5)	0.84	0.91	−0.20 (−0.91)	−0.07 (−0.71)	0.69 (8.9)	0.84
	Yes	No	545	0.22 (2.46)	0.32 (21.2)	0.45	0.67	0.23 (2.58)	0.06 (2.14)	0.29 (12.7)	0.46
Fixed Income	Yes	Yes	0								
	Yes	No	355	0.39 (3.50)	0.09 (6.9)	0.12	0.34	0.33 (3.01)	0.13 (4.32)	0.04 (2.7)	0.16
Emerging Markets	Yes	Yes	0								
	No	No	376	0.48 (1.84)	0.42 (13.1)	0.31	0.56	0.44 (1.72)	0.20 (2.57)	0.31 (6.0)	0.33
Macro	Yes	Yes	26	−0.45 (−0.56)	0.51 (4.9)	0.50	0.71	−0.49 (−0.65)	−0.45 (−1.83)	0.79 (4.4)	0.57
	Yes	No	158	−0.69 (−2.63)	0.34 (8.4)	0.31	0.56	−0.66 (−2.52)	−0.17 (−1.88)	0.44 (6.5)	0.33
	No	Yes	26	−0.45 (−0.56)	0.51 (4.9)	0.50	0.71	−0.49 (−0.65)	−0.45 (−1.83)	0.79 (4.4)	0.57
	No	No	845	0.93 (5.63)	0.26 (10.4)	0.11	0.34	0.93 (5.71)	−0.24 (−3.85)	0.39 (9.3)	0.13

Chapter 2

Market Timing with ETF Options[1]

In this chapter I provide new evidence on market timing by studying ETF option holdings of hedge funds. I find that market option holdings are economically significant in terms of their impact on the market exposure of the funds. Further, I find significant time variation in market option holdings, which could be due to market timing activity. I find that market option holdings are associated with such fund characteristics as active share and market exposure of the fund due to its stock holdings; this evidence is consistent with options being used for hedging. Increases in aggregate hedge fund industry holdings of market put options predict low market returns. In the cross-section of hedge funds, the top 5% group has market volatility timing skill that is distinguished from luck with a bootstrapping test. Additionally, I measure market timing ability as the average risk-adjusted return on market option holdings, which, due to data limitations, requires additional assumptions about option prices. I find that this market timing ability is close to zero for the average fund but it is negative for heavy option users.

[1] I thank Donghyun Kim for his contribution to the sample construction for this chapter. Donghyun was a PhD student at the University of Texas.

2.1 Introduction

Performance of an investment manager is commonly separated into security selection and market timing. While still a subject of continued academic debate, there is evidence that some mutual funds and hedge funds possess security selection skill. Market timing has also been thoroughly evaluated in the literature, but evidence of market timing skill is rather limited. There is evidence that hedge funds possess better investment skill than mutual funds. Therefore it is plausible that they also have a significant market timing skill. Hedge funds also have better tools for market timing than mutual funds. Most mutual funds can change their market exposure only by switching between high and low beta stocks, and a smaller set of mutual funds have a mandate allowing for asset allocation between stocks, bonds, and cash. Hedge funds can time the market more aggressively using futures and options to place highly-levered bets on the market, as well as against the market.

However, the use of options by hedge funds also presents a challenge for performance attribution and evaluation of market timing skill. Traditionally used measures of market timing are return-based. They evaluate the convexity of the relationship between market returns and returns of the fund. Hedge funds can buy this convexity by passively holding options since convexity with respect to market returns is a feature of options. The price of the convexity is option premium. Therefore, the convexity of hedge fund returns should not be used as a measure of market timing ability. Holdings-based measures of market timing have been applied to equity holdings of mutual funds and hedge funds. However, for hedge funds equity is an inefficient instrument for market timing. Instead, I evaluate the market timing ability of hedge funds based on their market option holdings.

For the first time in the literature, I construct a sample of market option holdings of hedge funds. I start with a unique unbiased sample of all hedge funds that are required to disclose their holdings to the SEC via form 13F. From original 13F filings of these hedge funds I extract their portfolio holdings of market ETF options, such as call and put options on SPDR S&P 500 ETF.

I find that market option holdings of hedge funds are significant. Market option use is widespread. Half of the funds held market options in at least one quarter and in every quarter 11%-24% of funds held market options during the sample period 2005–2014. Market option holdings are large enough to significantly alter the market exposure of funds. Changing over time, market exposure through market options is 2%-8% of portfolio value for hedge funds in aggregate, 4%-28% for the average fund. There is a substantial variation in market option weights at quarterly frequency, which may be due to market timing activity. I find that market option holdings are associated with such fund characteristics as active share and market exposure of the fund due to its stock holdings; this evidence is consistent with options being used for hedging. Increases in aggregate hedge fund industry holdings of market put options predict low market returns. In the cross-section of hedge funds, the top 5% group has market volatility timing skill that is distinguished from luck with a bootstrapping test.

Additionally, I measure market timing ability as the average risk-adjusted return on market option holdings, which, due to data limitations, requires additional assumptions about option prices. The average fund has a statistically insignificant market options return. This return is small in magnitude and its sign depends on the choice of benchmark for risk adjustment of option returns. In the sample of funds that hold a meaningful amount of options in many quarters, the average fund has a market timing return that is statistically significant, negative, and close to 0.40% per month; however, even the sign of the timing is sensitive to the choice of benchmark.

In a related paper, Aragon and Martin (2012) examine common stock option holdings of hedge funds reported in 13F. They find that a common stock's volatility and return are predicted by the fraction of hedge funds holding puts on it among all hedge funds holding that stock or an option on it. Their findings are limited to the dot-com bubble years 1999-2001 and are affected by survivorship bias. They rely on a sample of 77 hedge funds identified among 13F filers using TASS hedge fund database, which has been shown by Aggarwal and Jorion (2010) to be affected by survivorship bias in the coinciding period of 1999-2001. In the present paper I study market timing and, therefore, I study ETF options holdings. My hedge fund sample was constructed to include all hedge funds that filed 13F and to specifically address survivorship bias.

In the related literature on market timing, Chen and Liang (2007) use return-based market timing measures and find evidence of successful market timing by hedge funds that self-describe as market timing funds. To address the concern about return convexity arising from passive option holdings, they include two robustness tests. They test the difference in market timing between option users and option non-users, but the results are mixed and statistically insignificant due to the small subsample of funds with available information on option use. They also include market option factors in the estimation of the return convexity, and the estimates remain unaffected; however, this estimation does not control for the time variation in funds' market option exposure. The present paper is dedicated to the timing mechanism that it only addressed with robustness tests in their paper. Jiang, Yao, and Yu (2007) use a holdings-based market timing measure and find positive market timing ability for the average mutual fund. Elton, Gruber, and Blake (2012) evaluate market timing by mutual funds using self-reported holdings data that has monthly frequency and includes other asset classes in addition to equity. My paper is different from the above as it studies hedge funds and focuses on holdings of market options, which are more powerful market timing tools.

The rest of the chapter is organized as follows. Section 2.2 describes data sources, specifically for hedge fund option holdings data. Section 2.3 documents significance of market option holdings and the significance of their time variation. Section 2.4 explores determinants of market option holdings including fund characteristics and market conditions. Section 2.5 evaluates market timing of hedge funds based on their ability to adjust their option holdings before changes in market conditions. Section 2.6 evaluates market timing of hedge funds based on returns they earn on their market option holdings. Section 2.7 concludes.

2.2 Data

The data on option holdings comes from raw 13F filings available through the SEC's EDGAR website. The filings are available in electronic format through EDGAR since 1999 while hardcopy filings are available from SEC since 1978. Form

13F is filed by money managers on a quarterly basis. The form discloses firm-level holdings of those securities that are included in the official list of 13F securities. The list of 13F securities is updated on a quarterly basis. The list includes common stocks, preferred stocks, bonds, ETFs, ADRs, options, and warrants. The equity part of 13F data is processed by Thomson Financial into the commonly-used institutional ownership database S34. In this paper I focus on market ETF option holdings, such call and put options on SPDR S&P 500 ETF, ticker SPY. While market futures and market index options, such as SPX, are important instruments for market timing, they have not yet been included in the list of 13F securities.

I identify broad market ETF options in 13F data as follows. I merge all option holdings extracted from 13F filings with the CRSP stock names database and use CRSP share code 73 to identify ETF shares. For each ETF option, I calculate the value of the underlying ETF shares aggregated over all 13F filers. I use the aggregate underlying value to select only ETF options that are widely held in at least one quarter. Having selected a manageable list of ETF options, I manually check whether ETFs track a broad market index. The list of market ETFs included in my sample is presented in Table 2.2.

A comprehensive and unbiased sample of hedge fund firms filing form 13F is constructed as in Chapter 1 of this dissertation. The number of funds by year is presented in Table 2.1. Sample size increases from 179 firms in 1999 to 613 firms in 2008. There is an artificial decrease in the number of funds since 2011 because the sample has not yet been updated to include funds that first started reporting after 2011. Table 2.1 shows that close to half of the funds are market option users; those are the funds that held market options in at least one quarter. While the proportion of market option users remains significant throughout the sample period, there are few funds that actually hold options early in the sample period. The sparse use of options early in the sample has an exogenous component. The most widely held and actively traded options, puts and calls on SPDR S&P 500 ETF, first started trading on CBOE in 2005. Prior to that, NASDAQ 100 options have been traded since the 1990s, but they were only included in the official list of 13F securities in 2002. In order to have a meaningful cross-section of option holders throughout the sample period, I choose the sample period to be 2005-2014.

2.3 Significance of Market Option Holdings

The first finding of this paper is that market option holdings are significant. The contribution of an option position to the fund's return and to the fund's market beta is approximately equal to the ratio of the value of the underlying to portfolio value. This is because the option price in the numerator of the option portfolio weight is replaced by the underlying price when the weight is multiplied by the option return leverage. Option delta can significantly reduce the impact of the option on the fund return, especially for deep-out-of-money options. However, most options are traded at the money and have delta on the order of 0.5 and when they expire in the money their effective delta is 1. Therefore, it is convenient to measure the significance of option holdings by the underlying value ratio.

Table 2.3 presents the contribution of market options to the return and market beta of the average fund, as approximated by the underlying value ratio. Underlying values of puts and calls are summed up together, resulting in a gross exposure measure. In aggregate, the underlying value ratio varies between 1.7% and 7.9% in the 2005–2014 sample period. For the average fund, the impact of market options on beta varies from 3.7% to 28.1%. Among the funds that held market options in at least one quarter, the impact of market options on beta of the average fund varies from 5.5% to 39.1%, and it is above 20% during most of the sample period.

Table 2.4 describes the cross-sectional distribution of market option holdings. Among the option users, which constitute approximately half of the sample, about 10% to 20% of funds have substantial market option holdings. Given that the number of option users varies from 200 to 302, as seen in Table 2.1, in every quarter there are 20 to 60 funds with substantial option holdings. For 5% of option users in 2010-2013, contribution of market options to the fund beta is greater than 1.

Time variation in market option holdings is also significant, which might be an indication of market timing activity. When option weight data is presented at annual frequency, as in Table 2.3 and Table 2.4, quarterly variation is smoothed out, and only the general inverted-U shape trend is observed. Figure 2.1 and Figure 2.2 present the same data at quarterly frequency and reveal a significant time variation. Figure 2.1 shows that, for the average fund, market option weight has several single quarter changes of 5%-10%. Figure 2.2 shows time variation of cross-sectional option weight percentiles. The percentiles also display time variation that is comparable to their average levels. Most dramatically, the 90th percentile has several single-quarter changes of over 30%.

2.4 Determinants of Market Option Holdings

I explore fund characteristics that could be associated with market option use. Panel A of Table 2.5 presents results of univariate regressions of market option weight on fund characteristics. Option weight is calculated as the underlying value divided by the sum of stock values and underlying option values held by the fund. Weights and fund characteristics are winsorized at 1% level. Market options weight of a fund is the sum of weights of the market ETF options listed in Table 2.2.

Market beta of the fund that results from stock holdings is associated with option weights consistent with hedging. Funds with high stock beta tend to hold more market puts. In addition to fund beta resulting from stock holdings, I investigate beta resulting from options on common stocks, which do not include ETF options. The beta of stocks and stock options is associated with negatively associated with call option holdings, which is also consistent with hedging. However, the call weight coefficient is only marginally significant and the put weight coefficient is far from significance. The relationship being weak might be due to a separate mechanical relationship between market option weight and stock option weight. The definition of market option weight has the underlying value of stock options in the denominator, resulting in negative mechanical relationship between the weights. To evaluate significance of this mechanical channel, I regress market option weight on stock option weight. Stock option weight is strongly and positively associated with call weight and put weight, indicating that the mechanical channel is not particularly strong. Funds that use stock options also tend to use market options.

Active share of a fund is associated with option holdings in way that is consistent with active managers hedging their factor risk exposure. Active managers hold more options as measured by gross weight. Net weight has a negative sign indicating market hedging. Other measures of manager activeness, such as Herfindahl index and turnover also provide evidence consistent with this intuition. Titman and Tiu (2011) argue that managers that are able to generate alpha should hedge their systematic risk exposure in order to maximize Sharpe ratio.

Mean stake coefficients show that funds that take large ownership stakes in companies tend to use fewer market options. This is consistent with funds following distinct investment strategies. Specifically, activist investors specialize in influencing business of the companies the invest in but might be less active in making market bets or managing their market exposure. This intuition is corroborated by the call weight coefficient on average market capitalization of stocks held by a fund. It indicates that funds that hold smaller stocks use fewer call options. However, somewhat contradictory, funds holding less liquid stocks tend to hold more call options. One possible explanation is that funds with illiquid stocks wishing to manage their market exposure might prefer to use market options because sector rotation and trading in and out of high and low beta stocks might be too expensive.

I also consider fund age, fund size, and past returns of the fund because these are exogenous fund characteristics in the sense that they are not chosen by the fund manager. Fund age, fund size, and past returns can be related to reputation concerns and incentives for herding and risk shifting using market options. In univariate tests, fund age is not significantly related to market option holdings. Fund size, which is measured by the value of its stock portfolio, is negatively associated with both call and put weights. However, this relationship might be mechanical as the stock portfolio value enters the denominator of an option weight. Funds that performed poorly over the previous four quarters hold more calls which is consistent with risk shifting by taking on market risk.

I test whether significant univariate results survive in a multivariate regression. Panel B of Table 2.5 reports multivariate tests results. Most univariate results survive essentially unchanged in the multivariate setting. Mean stake results become much weaker and insignificant, but do not change their signs. Fund size results hold for call weight but become insignificant for put weight.

I also report results of tests that include fund fixed effects. The goal of including fund fixed effects is to remove bias due to committed variables that are relatively constant over time. However, the downside is the loss of test power coming from the cross-section. Because fund characteristics are likely stable over time, test power might be too low once fixed effects are included. In univariate setting, only two fund characteristics remain significant with fixed effects: beta of stocks and liquidity. In multivariate setting with fund fixed effects, liquidity remains significant, while beta of stocks preserves the signs but falls below significance.

I further investigate the relation between option use and incentives for risk shifting. Panel C of Table 2.5 focuses on year-to-date performance interacted with month dummies. The results show that year-to-date performance is significant when it is interacted with December dummy but it is not significant when interacted with other quarter-end dummies. This is consistent with winners (losers) decreasing (increasing) their market risk exposure at the year-end. This interpretation assumes that the option holdings observed at the end of December have been established earlier in the last quarter and the hedging effect of these options is reflected in fund returns before option maturity due to mark-to-market accounting.

Next, I evaluate whether market option holdings are explained by contemporaneous market conditions. To this end, I regress aggregate market option weight on contemporaneous market return and change in VIX. Results are presented in Table 2.6. Market put weight of the average fund at the end of a quarter is positively correlated with market return during that quarter. This can be interpreted as a contrarian behavior by the average hedge fund. This test does not find any significant correlation between option weights and contemporaneous changes in VIX.

2.5 Market Timing Tests without Option Price Assumptions

The ability to time the market using market options should be evaluated based on returns earned on market option holdings. However, 13F does not provide option prices or sufficient details on option holdings to match them to an option price database. One approach, which I pursue in the next chapter, is to make additional assumptions on option maturities and strike prices. These assumptions are justified on the basis that trading of market options is dominated by contracts with certain characteristics. Another approach, which I pursue in this chapter, is to set aside the questions related to the loss of option premium and option leverage, and instead focus on the ability of hedge funds to predict market returns and changes in VIX, which is a necessary condition for market timing.

To test whether market option holdings of hedge funds predict the market, I regress market return and VIX changes on lagged option weights or lagged option weight changes. Since VIX is calculated as implied volatility of S&P 500 options, I use only S&P 500 ETF options (ticker SPY) and I use return on S&P 500 ETF as the market return. Market options weight in a fund portfolio is calculated as the ratio of the underlying value to the sum of stock portfolio value and the underlying value of all options held by the fund. This definition ensures that the weight is between 0 and 1 and that it is robust to outliers. I also winsorize option weights at 1% level.

2.5.1 Aggregate and Average Market Timing

I test wether the level or changes in market option holdings of hedge funds predict market returns and changes in VIX. The results are presented in Table 2.7. I find that changes in aggregate put holdings predict market returns. Quarters during which hedge funds in aggregate increase market put holdings are followed by quarters with low market returns. Aggregate call weight changes do not have statistically significant predictive power. This might be due to the smaller sample size of call options; in untabulated summary statistics, hedge funds holdings of market puts are much more substantial than holdings of market calls. The changes of net weight of calls and puts are marginally significant in predicting market return. The changes of gross weight of calls and puts are highly significant in predicting market return.

Market timing of the average fund, which is calculated with equal-weighted option holdings across funds, is insignificant. The contrast between the aggregate and average fund results indicates that market timing ability is concentrated among large funds. This is consistent with the incentive of large funds to pursue strategies with high capacity.

VIX changes are not predicted by aggregate or average option holdings of hedge funds. However, VIX predictability is found in a sample of hedge funds that follow global macro strategy, as is discussed in the following chapter. Further, in the cross-section of hedge funds, there is statistically significant evidence that a small group of funds is able to time VIX with options.

2.5.2 Global Macro Funds

I separately evaluate market timing ability of hedge funds that pursue Global Macro investment strategy. Global Macro is defined as an investment strategy based on the analysis of macro economic trends around the globe across asset classes. For these tests I calculate market options portfolio weight based on total hedge fund firm assets under management instead of the value of the firm's 13F portfolio, as in all other tests. In other tests, I use the firm's 13F assets in the denominator of portfolio weights because the firm's total AUM data is not readily available. For many firms this is a good approximation. However, for Global Macro firms the approximation is likely poor. Because these firms are particularly interesting in a market timing study, I collect these firms' AUM data.

I identify 38 Global Macro hedge funds among 13F filers in 2005-2015 period. This sample is not exhaustive, i.e. there might be other Global Macro funds among 13F filers. For the identification, I rely on two hedge fund databases, HFR and BarclayHedge, as well as on Factiva archive of press publications. In addition to these sources, I use SEC Form ADV to collect annual data on firms AUM. Unfortunately, the sample construction procedure is not proof of the survivorship bias and the self-reporting bias.

Table 2.8 presents results of the market timing tests for the sample of Global Macro funds. The average fund is able to time the market return and VIX using call options. Statistical significance is particularly high in the VIX-on-gross regression with the t-statistic of 4.51. Both call weight changes and put weight changes predict positively predict VIX changes. Call options also have marginally significant predictive ability in all other specifications, with aggregate or average weights and with weight levels or weight changes. The net of calls and puts is insignificant in predicting VIX.

The market return is predicted by both call and put weights equal-weighted across funds. Increase in put holdings predicts low market return. This is clearly consistent with market timing since put value of a put increases when the underlying price decreases. Increase in call options also predicts low market return. Whether this should be interpreted as a successful market timing depends on the benchmark. A call value decreases as the underlying price decreases. Therefore, holdings a call generates lower returns than a market neutral position during market downturns. However, a call value decreases slower than the value of the underlying, and an out-of-money call is insensitive to negative market returns. Thus a call position represents a successful market timing when the alternative is holding the market.

In the aggregate holdings test, which value-weights the funds, call timing results are consistent but weaker and put timing results are close to zero. This indicates, that in the sample of Global Macro funds smaller funds have higher market timing ability.

2.5.3 Cross-Section of Market Timing

In this section I investigate how large is the group of hedge funds that are able to time the market. I estimate market timing for each fund separately and then analyze percentiles of the cross-sectional distribution of market timing. Table 2.9 presents the results. The percentiles of the distribution of t-statistics are presented in parentheses. T-statistics greater than 2.00 in magnitude can be found only 5^{th} and 95^{th} percentiles. This implies that the groups of funds with significant positive or negative market timing are small. Market volatility timing is positive and highly significant for the top 5% of funds both with calls and puts. The significant negative t-statistic at the 5^{th} percentile of the VIX-on-net coefficient means that put holdings increase more than call holdings prior to VIX increases. This finding is harder to interpret but it is consistent with the timing ability found separately for calls and puts. Marginally significant negative t-statistics are found on the call coefficient both in the return and volatility regressions. This might imply that there are funds with negative market timing ability, but more likely this marginal t-statistics can be explained pure chance or estimation noise. I will address statistical significance of the described here percentiles in the following section using a bootstrapping estimation.

I also repeat the cross-sectional analysis using option holdings levels instead of changes. The results are presented in Table 2.10. They are generally consistent with the changes results, but there is stronger evidence of negative market timing with both calls and puts.

2.5.4 Bootstrapping Test of Cross-Sectional Findings

I employ a bootstrapping test to formally evaluate statistical significance of the cross-sectional findings. Specifically, I test whether the observed cross-sectional percentiles of timing ability can be explained by pure chance. I generate many random cross-sectional percentiles of timing ability and calculate how frequently they fall above the observed percentiles.

In order to preserve correlations in option holdings across funds and autocorrelations, the panel of option weights remains the same as the empirically observed panel across all iterations of the simulation. However, the time-series of market returns and VIX changes is randomly permuted at each iteration. Since returns and VIX sequences are random, the simulation yields the distribution of market timing estimates that is the result of pure chance without underlying true market timing ability. For each permutation of market returns and VIX I estimate market timing for each fund and calculated cross-sectional percentiles. I repeat the permutation and the estimation 1,000 times and obtain 1,000 simulated values for each cross-sectional percentile of interest. I then calculate right (left) p-values of the simulated percentiles as the fraction of simulated percentiles that are above (below) the empirically observed percentiles.

Results of the bootstrapping test are presented in Table 2.11. The test confirms statistical significance of the cross-sectional findings on market timing. 95^{th} percentile is significant for volatility timing with calls and and marginally significant for timing with puts. Negative market return and VIX timing at the 5^{th} percentiles are indistinguishable from bad luck. Table 2.12 presents results of the bootstrapping test with holdings levels instead of holdings changes. This test shows that both 5^{th} and 95^{th} percentiles are insignificant for market return timing and for volatility timing. Marginal significance is found for the market return timing with gross weight, and for VIX timing with put weight and with gross weight.

2.6 Market Timing Tests under Option Price Assumptions

2.6.1 Option Prices

I make simplifying assumptions to calculate option prices and returns. The 13F data on options holdings does not include information on option price, expiration date, and strike price. However, about 20% of the observations do include voluntarily a reported option price. This subsample could be further explored, but for most observations some assumptions are necessary. I assume that all options are at the money, expire in one month, have implied volatility of 20%, and that the risk-free rate is 3%. Based on this, the Back-Scholes formula yields a convenient result that option price is equal to the underlying ETF price multiplied by a constant, 0.02 under the chosen parameters.

$$C = P = 0.02S$$

$$\ell = S/C = S/P = 50$$

where C is a call price, P is the put price, S is the underlying ETF price, and the equations are approximate; the second line introduces the notation ℓ for the price ratio, which is related to option leverage but is not equal to the ratio of returns.

The assumptions are justified as follows. Using the OptionMetrics database, I confirm that option trading and open interest are dominated by options that are near-the-money and have less than two months to maturity. Further, CBOE market options expire on the third Friday of the month, resulting, for most options, in a fixed time to maturity from the 13F reporting quarter-end. While assumptions on maturity and moneyness are necessary, the remaining assumptions are for simplicity. Having assumed maturity and moneyness, option prices can be obtained from OptionMetrics.

Return on an option holding is calculated under the following assumptions. Options are assumed to be held to maturity and the expiration date is assumed to be in one month from the quarter-end of 13F reporting. I assume that the strike price is equal to the underlying ETF price on the quarter-end of 13F reporting, i.e. the option is at the money, as is also assumed in the option price calculation. Under these assumptions, option payoff is determined by the price of the underlying ETF. If underlying price reduced since the quarter-end, then call option payoff is 0 and option return is -100%, due to the loss of premium. If the price of the underlying increased since the quarter-end, then call option payoff is equal to the underlying price increase and option return is equal to -100% due to the loss of premium plus the underlying return multiplied by the ratio of initial prices of the underlying and the option.

$$r_{call} = -1 + I(r_m > 0) r_m S/C$$

$$r_{put} = -1 - I(r_m < 0) r_m S/P$$

where r_m is the underlying market ETF return and I is the indicator function. Under the standing assumptions about the option price at the quarter-end, the above equations can be combined as

$$r_{call/put} = -1 \pm I(\pm r_m > 0) r_m \ell$$

2.6.2 Measures of Market Timing

I measure market timing ability as average risk-adjusted return on market option holdings.

$$MT = \overline{\omega_t(r_t - r_{bench,t})}$$

where ω_t is portfolio weight of the market option, r_t is the option return, $r_{bench,t}$ is a benchmark return, and the overline denotes time average. Market timing with multiple options is calculated as a sum of single-option MT over all options. The sum accounts for calls and puts on the same market ETF, as well as for multiple market ETFs.

I consider multiple benchmarks for risk adjustment. A natural alternative to market timing with options is holdings market options with a constant weight. This alternative investment corresponds to a benchmark return equal to the average option return $r_{bench,t} = \overline{r}$ as seen from the following

$$MT = \overline{r_t(\omega_t - \overline{\omega})} = \overline{r_t\omega_t} - \overline{r_t\bar{\omega}} = \overline{r_t\omega_t} - \bar{r}\bar{\omega} = \overline{r_t\omega_t} - \overline{\bar{r}\omega_t} = \overline{\omega_t(r_t - \bar{r})}$$

This measure is equal to covariance of option weight with option return $\text{Cov}[\omega_t, r_t]$ and is proportional to the slope in the regression

$$\omega_t = \gamma r_t + \alpha + \epsilon_t$$

Thus, this measure has the intuitive interpretation: market timing is positive if high option weight is followed by high option return.

Another plausible benchmark is the market. If the benchmark investment strategy holds the market with a constant weight, then

$$MT = \overline{\omega_t(r_t - \overline{r_m})} = \overline{\omega_t(r_t - r_m)} + \overline{\omega_t(r_m - \overline{r_m})}$$

The decomposition above is intuitive. The first term is market timing with the benchmark being the market with time-varying weight. This term can be interpreted as timing the choice of ETF option versus ETF stock. The second term is the covariance of market return and the weight. This term can be interpreted as timing of market return only by varying weight without switching between ETF stocks and ETF options.

The following two measures address the fact that market risk exposure of an option is not equal to 1. Conditional on market return, option betas are

$$\beta_{call}|r_m > 0 = S/C = \ell$$

$$\beta_{call}|r_m \leq 0 = 0$$

$$\beta_{put}|r_m > 0 = 0$$

$$\beta_{put}|r_m \leq 0 = -S/P = -\ell$$

The first β-adjusted measure sets option β the average of conditional β's.

$$MT = \overline{\omega_t(r_t - \overline{\beta_A r_m})} = \overline{\omega_t(r_t - \beta_A r_m)} + \overline{\omega_t(\beta_A r_m - \overline{\beta_A r_m})}$$

$$\beta_A = \begin{cases} \ell/2 & \text{for call} \\ -\ell/2 & \text{for put} \end{cases}$$

The second measure sets option β to the corresponding downside β.

$$MT = \overline{\omega_t(r_t - \overline{\beta_D r_m})} = \overline{\omega_t(r_t - \beta_D r_m)} + \overline{\omega_t(\beta_D r_m - \overline{\beta_D r_m})}$$

$$\beta_D = \begin{cases} 0 & \text{for call} \\ -\ell & \text{for put} \end{cases}$$

2.6.3 Market Timing of the Average Fund

Market timing measures for the average fund are presented in Table 2.13. The results are presented for two samples of funds, option users and heavy option users. Option users are the funds that held market options in at least one quarter. Thus, this sample excludes funds that never use market options. The sample of heavy option users only includes funds that held market options with the value of underlying of at least 10% of the value of the total fund portfolio in at least 10 quarters. Thus, this sample excludes funds that do not use market options, funds that use the options infrequently, and funds with option holdings that are too small to substantially alter fund market exposure. Market timing is first calculated for each fund-quarter observation, and then a pooled equal-weighted mean is calculated over fund-quarter observations.

Market timing of option users is slightly negative according to most measures, and has an economically insignificant magnitude not exceeding 11 basis points per month. In contrast, downside-β measures are positive, as these measures fully incorporate the benefit of an option's market hedging feature. The downside-β measure with $\beta_D r_m$ benchmark is equal to an economically significant 25 basis points per month. This measure accounts only for the timing of option-stock choice and does not account for timing the benchmark $\beta_D r_m$. When the benchmark timing is also accounted for, the timing measure reduces to 9 bps/month.

In the sample of heavy option users market timing is economically significant, ranging in magnitude from 18 to 70 bps/month, depending on the measure, with only one measure having a smaller magnitude of 5 bps/month. Market timing of heavy option users is negative according to most measures, with the notable exception of downside-β measures. The downside-β measure with $\beta_D r_m$ benchmark is 70 bps/month. These results show that market timing is economically significant for funds that hold substantial market option holdings, but the results are sensitive to the choice of benchmark.

In order to evaluate the statistical significance of the average market timing, Table 2.13 presents both pooled and Fama-MacBeth t-statistics. Pooled t-statistics indicate significance of most timing measures, both for option users and for heavy option users. However, the pooled t-statistics may be inappropriate if the cross-section of returns on option holdings, $\omega_t(r_t - r_{bench,t})$, are correlated. The option return part is the same for all funds in the cross-section as, by assumption, all options are identical in terms of their maturity and moneyness. It is not obvious, however, whether options weights are strongly correlated across funds. The estimated Fama-MacBeth t-statistics are much smaller than the pooled t-statistics, signaling significant cross-correlation in option weights. Market timing is significant only in the sample of heavy option users and only with unadjusted or market-adjusted measures. These measures are also economically significant and negative.

Overall, there is marginal evidence of negative market timing by the average fund. Among the funds with substantial option holdings, market timing is economically significant. It is also statistically marginally significant when market return is used as a benchmark. However, statistical significance and even the sign of the estimates are sensitive to the choice of benchmark.

2.6.4 Market Timing in the Cross-Section

Cross-section distribution of market timing is presented in Table 2.14. Market timing and its t-statistics are first estimated for each fund, and then percentiles of market timing and percentiles of t-statistics are calculated for the cross-section of funds. The estimation is restricted to the sample of funds that held market options in at least 10 quarters in order to have meaningful single-fund estimates.

The timing of the median fund is slightly negative according to most measures, has an economically small magnitude of less than 10 bps/month, and is statistically insignificant. On the right side of the distribution, timing magnitude is positive and economically significant for all measures for only the top 5% of funds. However, t-statistics are below 2.00 even for the top 1% of funds. Notable exceptions are the timing measures with a ownside-β benchmark. They are economically significant for top 20% funds and the constant-weight measure has t-statistic of 2.00 for the top 5% of funds and 2.92 for the top 1% of funds, which cannot be explained by pure noise and merits further investigation.

On the left side of timing distribution, evidence of significant negative market timing is more substantial. Timing is economically significant for the bottom 10% funds with magnitudes above 27 bps/month for all measures except downside-β

measures, which become significant at the 5th percentile. Unadjusted and market-adjusted measures are particularly large, about -80 bps/month for bottom 10% funds and -135 bps/month for bottom 5% funds. The bottom 5% of funds have t-statistics larger than 2.00 for most measures, and larger than 3.00 for unadjusted and market-adjusted measures.

The large magnitudes and t-statistics in the left tail of market timing motivate a more rigorous statistical test in order to distinguish between truly poor market timing activity and bad luck. I estimate bootstrapped p-values for the cross-sectional percentiles observed in the data. The bootstrapping simulation is designed so that there is no correlation between market return and option weights in fund portfolios.

In each iteration of the simulation, I draw without replacement monthly market returns from the set of empirically-observed market returns and thus construct a simulated history of market returns that is a random permutation of the empirically observed sequence. Based on the simulated history of market returns, I calculate a history of option returns. I do not simulate option portfolio weights; instead I use the empirically observed history of option portfolio weights in every simulation. I then calculate market timing measures for every fund using the simulated history of option returns and the empirical history of option portfolio weights. Option weights are independent of market returns due to the fact that market returns are randomly selected. Therefore the resulting cross-sectional distribution of market timing is random and unrelated to market timing ability of funds. Funds in the tails of this distribution have extreme market timing measures purely due to luck, and the extreme measures do not indicate market timing ability.

In each iteration of the simulation, I calculate the percentiles of the cross-sectional distribution of market timing t-statistics. Repeating the simulation many times, I obtain a large set of simulated values for each cross-sectional percentile. Then left (right) p-values of empirically observed percentiles are calculated as the percentage of simulated percentiles that are below (above) the empirically observed percentiles.

Bootstrapped p-values of the cross-sectional percentiles are presented in Table 2.15. The results in the table are for 1000 iterations of resampling. The table presents left p-values; therefore, p-values below 0.05 indicate significantly bad market timing and p-values above 0.95 indicate significantly good market timing. Only one p-value, corresponding to the 1st percentile and a downside-β measure, is above 0.95, indicating that under this measure the worst 1% of market timers are not as bad as would be expected by pure chance. Thus, this test provides no evidence of significant positive market timing.

Almost all percentiles of downside-β and average-β measures fall well above 0.05 and well below 0.95. Thus, these measures provide no evidence of significant positive or negative timing. The unadjusted, fixed-weight-adjusted, and market-adjusted measures have p-values below 0.10 for most percentiles indicating that the distributions of these measures are shifted to the left compared to the random distribution. P-values below 0.05 indicate that the top 1% funds and the median funds have worse market timing than would be expected due to chance. Under these measures, p-values of the 10th, 5th, and 1st percentiles are in the range 0.05-0.08. These p-values provide marginally significant evidence that a large group of funds exhibit statistically significant negative market timing.

2.7 Conclusion

In this chapter I study market ETF option holdings of hedge funds. I start with a sample of all hedge funds that report to 13F and extract their option holdings directly from raw 13F filings. I document that market option holdings of hedge funds are economically significant and can alter a fund's market risk exposure. I find that market option holdings are associated with such fund characteristics as active share and market exposure of the stock portfolio. Increases in aggregate hedge fund industry holdings of market put options predict next quarter market volatility increases and negative market returns. In the cross-section of hedge funds, the top 5% group has market volatility timing skill that is distinguished from luck with a bootstrapping test.

Figure 2.1: Time Variation of Cross-Sectional Mean of ETF Option Holdings

This figure plots cross-sectional means of ETF option holdings weights versus time. The top graph plots equal-weighted mean and the bottom graph plots value-weighted mean. The options weight in a fund portfolio is calculated as the underlying value of these options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. Underlying values of puts and calls are summed up together resulting in a gross weight. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. The mean is calculated over the sample of market option users, which are funds that held market ETF options in at least one quarter.

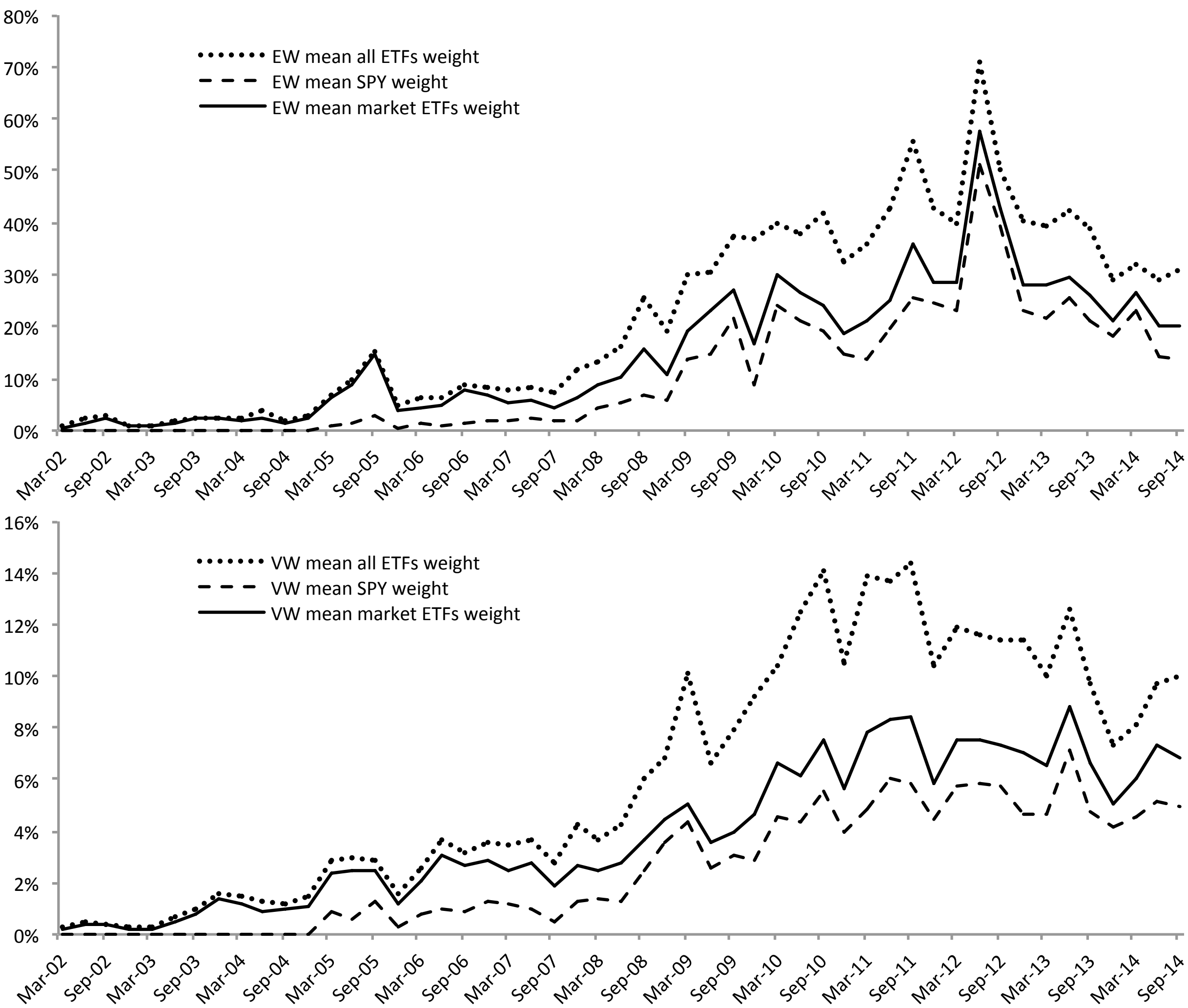

Figure 2.2: Time Variation of Cross-Sectional Percentiles of Market Option Holdings

This figure plots cross-sectional percentiles of ETF option holdings versus time. The options weight in a fund portfolio is calculated as the underlying value of these options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. Underlying values of puts and calls are summed up together resulting in a gross weight. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. The percentiles are calculated for the sample of option users, which are funds that held ETF options in at least one quarter.

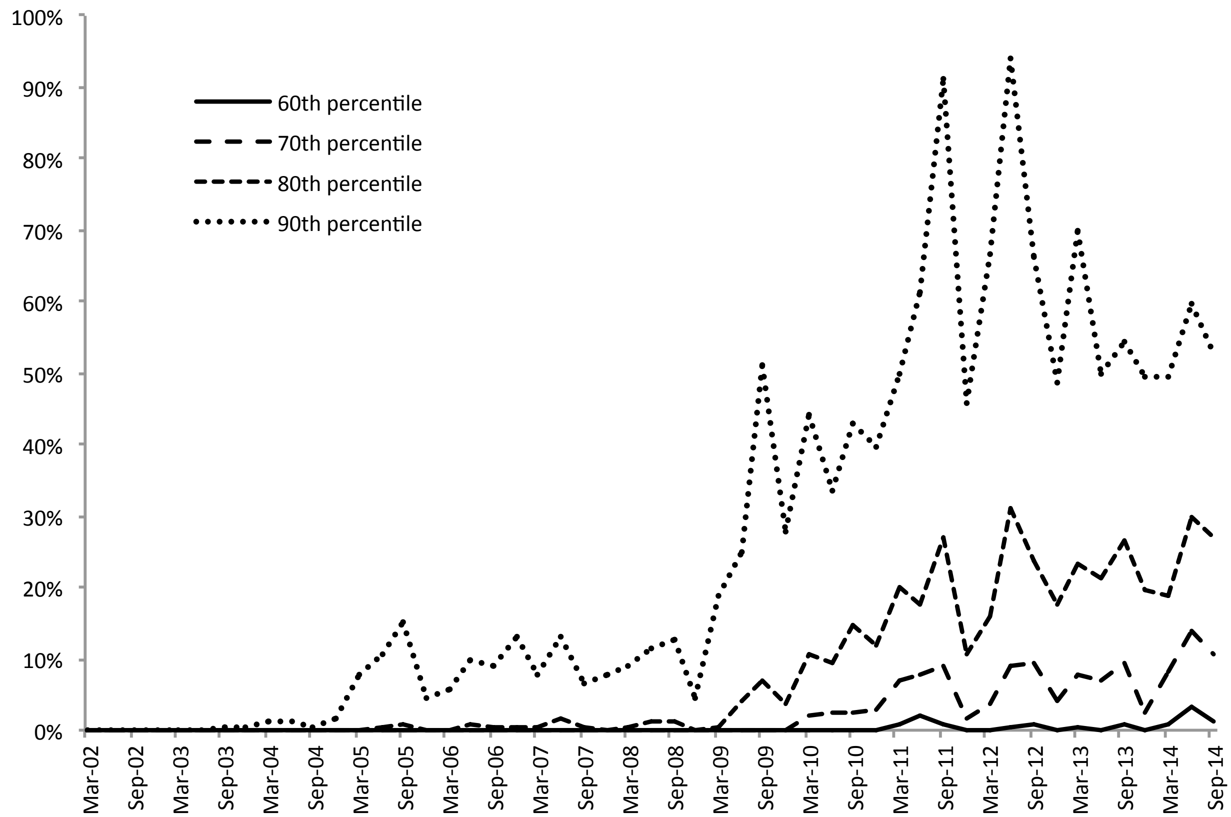

Table 2.1: Sample Size

This table presents the number of funds in the sample by year. *Users* column presents the number of funds that held market ETF options in at least one quarter. *Holders* column presents the number of funds that held market ETF options in the corresponding quarter. Calculations are first done for each quarter and then averaged over the four quarters of a year.

Year	All funds	Users	Users, %	Holders	Holders, %
1999	179	66	37	0	0
2000	220	80	36	1	1
2001	240	95	40	4	2
2002	251	109	43	10	4
2003	242	112	46	11	5
2004	325	157	48	24	7
2005	403	200	50	46	11
2006	487	240	49	62	13
2007	570	280	49	76	13
2008	613	309	50	73	12
2009	555	299	54	88	16
2010	528	287	54	112	21
2011	562	302	54	133	24
2012	513	285	56	120	23
2013	474	263	55	108	23
2014	450	246	55	110	24

Table 2.2: List of Market ETFs

This table presents a list of broad market ETFs that have call and put options included in the official list of 13F securities. This table omits a few market ETFs that are not widely held by 13F filers and are not included in my sample of market ETF options.

Ticker	Name	Index
SPY	SPDR S&P 500 ETF Trust	S&P 500
QQQ/QQQQ	PowerShares QQQ Trust/NASDAQ 100 Trust Series I	Nasdaq 100
IWM	iShares Russell 2000 ETF	Russell 2000
IVV	iShares Core S&P 500 ETF	S&P 500
IWN	iShares Russell 2000 Value ETF	Russell 2000 Value
DIA	SPDR Dow Jones Industrial Average ETF/DIAMONDS Trust	Dow Jones Industrial Average
MDY	SPDR S&P MidCap 400 ETF Trust	S&P MidCap 400

Table 2.3: Mean Option Holdings

This table presents the cross-sectional mean of ETF option holdings. The options weight in a fund portfolio is calculated as the underlying value of these options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. Underlying values of puts and calls are summed up together resulting in a gross weight. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. The presented means are equal-weighted except in the *All Funds, VW* column, where the mean is value-weighted. *Users* columns are based on the subsample of funds that held market ETF options in at least one quarter.

	All Funds		Users		
Year	EW	VW	All ETFs	Market ETFs	SPY
2002	0.7	0.2	1.7	1.3	0.0
2003	0.9	0.5	2.0	1.8	0.0
2004	1.3	0.8	2.6	2.0	0.0
2005	4.6	1.7	9.3	8.3	1.4
2006	3.7	2.2	7.4	5.9	1.4
2007	4.3	2.4	8.8	5.5	2.1
2008	9.6	3.4	18.5	11.3	5.7
2009	18.4	5.3	33.8	21.5	14.7
2010	20.9	7.4	37.9	24.7	19.7
2011	23.9	7.9	44.3	27.6	21.0
2012	28.1	7.0	50.3	39.1	34.1
2013	20.7	6.1	37.3	26.2	21.6
2014	16.8	5.8	30.8	22.2	17.1

Table 2.4: Cross-Sectional Distribution of Market Option Holdings

This table presents the cross-sectional mean of ETF option holdings. The options weight in a fund portfolio is calculated as the underlying value of these options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. Underlying values of puts and calls are summed up together resulting in a gross weight. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. The percentiles are calculated for the sample of market option users, which are funds that held market ETF options in at least one quarter.

	Percentiles					
Year	50	60	70	80	90	95
2002	0.0	0.0	0.0	0.0	0.0	3.7
2003	0.0	0.0	0.0	0.0	0.0	3.8
2004	0.0	0.0	0.0	0.0	1.1	7.8
2005	0.0	0.0	0.0	0.3	9.5	23.4
2006	0.0	0.0	0.0	0.4	10.0	22.7
2007	0.0	0.0	0.0	0.5	8.1	27.2
2008	0.0	0.0	0.0	0.5	9.8	41.1
2009	0.0	0.0	0.0	3.3	31.7	87.2
2010	0.0	0.0	2.2	11.0	38.9	114.4
2011	0.0	0.5	6.5	19.6	62.2	127.0
2012	0.0	0.2	6.5	21.1	68.4	145.6
2013	0.0	0.1	7.1	22.7	53.0	108.7
2014	0.0	1.3	10.7	26.0	55.8	89.9

Table 2.5: Determinants of Market Options Holdings

The table presents results of the following pooled regression:

$$\omega_{i,t} = \beta X_{i,t} + \epsilon_{i,t}$$

where $\omega_{i,t}$ denotes the weight of market options in the portfolio of fund i at time t; and $X_{i,t}$ denotes the vector of fund characteristics. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on broad market index ETFs. Weights and fund characteristics are winsorized at 1% level. *Beta of stocks* is the market beta of the fund that is due to stocks only excluding the beta contribution of options. *Beta of stocks and stock options* is the market beta of the fund that is due to stocks and stocks options excluding ETF options. *Liquidity* of a fund is the value-weighted average of its stocks liquidity, which is the volume-induced daily return reversal as in Pástor and Stambaugh (2003a). *Mean stake* is the value-weighted average of the fraction of stock's shares outstanding held by the fund. *Stock options weight* is the portfolio weight of common stock options, which does not include ETF options. *Log(market cap)* is the value-weighted mean of log of market capitalizations of stocks in the portfolio of a fund. $r_{i,t}$ is fund return from time $t-1$ to time t. $\overline{r}_{i,t}$ is geometric mean return since the beginning of holdings reporting. $r_{i,t}^{\mathrm{YTD}}$ is the year-to-date return. T-statistics, in parentheses, are two-way clustered by time and by fund. All coefficients are multiplied by 100. The sample period is 2005–2014.

Panel A: Univariate regressions

	Weight type							
	Call	Put	Net	Gross	Call	Put	Net	Gross
Beta of stocks	0.02	1.07**	−1.06**	1.25**	−0.05	0.54**	−0.62**	0.60
	(0.33)	(3.04)	(−3.06)	(3.05)	(−0.70)	(1.97)	(−2.36)	(1.78)
Beta of stocks and stock options	−0.14	0.12	−0.26	−0.10	−0.12	−0.38	0.22	−0.51
	(−1.94)	(0.42)	(−1.01)	(−0.27)	(−1.44)	(−1.61)	(0.98)	(−1.62)
Stock options weight	1.56**	5.73**	−4.34**	7.56**	−0.10	−1.41	1.15	−2.69
	(6.03)	(6.22)	(−5.48)	(6.58)	(−0.31)	(−1.21)	(1.19)	(−1.69)
Active share	−0.70	3.46**	−4.10**	3.62	0.54	0.70	−0.42	2.78
	(−1.68)	(2.23)	(−3.04)	(1.89)	(0.69)	(0.27)	(−0.18)	(0.80)
Herfindahl	0.40	1.62	−1.15	3.14**	0.40	0.17	0.31	1.34
	(1.48)	(1.51)	(−1.20)	(2.13)	(1.26)	(0.16)	(0.33)	(0.95)
Turnover	0.70**	2.58**	−1.91**	3.37**	0.18	0.02	0.14	0.20
	(3.85)	(3.52)	(−2.86)	(3.60)	(1.28)	(0.04)	(0.29)	(0.28)
Mean stake	−5.23**	−17.29**	12.50**	−25.79**	−0.70	−5.25	3.95	−6.97
	(−4.70)	(−2.91)	(2.29)	(−3.58)	(−0.41)	(−0.62)	(0.47)	(−0.76)
Log(market cap)	0.07**	0.07	0.00	0.16	0.05	0.14	−0.10	0.25
	(3.08)	(0.65)	(0.04)	(1.24)	(1.30)	(0.99)	(−0.78)	(1.46)
Liquidity	−0.25**	−0.33	0.17	−0.94	−0.17**	−0.11	0.00	−0.41
	(−2.09)	(−0.77)	(0.44)	(−1.51)	(−2.64)	(−0.30)	(0.00)	(−1.05)
Log(fund size)	−0.05**	−0.23**	0.18**	−0.40**	−0.04	−0.17	0.15	−0.30
	(−2.31)	(−2.32)	(2.07)	(−2.99)	(−1.33)	(−1.31)	(1.15)	(−1.76)
Log(age)	0.05	0.53	−0.48	0.62	0.04	−0.50	0.54	−0.37
	(0.84)	(1.62)	(−1.57)	(1.57)	(0.29)	(−0.86)	(1.00)	(−0.55)
$r_{i,t}$	−0.22	0.15	−0.47	−0.29	0.12	1.47	−1.44	1.61
	(−1.12)	(0.11)	(−0.35)	(−0.22)	(0.62)	(1.51)	(−1.39)	(1.75)
$r_{i,t-4,t}$	−0.33	−0.48	0.15	−0.97	−0.12	0.60	−0.70	0.52
	(−1.94)	(−0.68)	(0.21)	(−1.10)	(−0.92)	(1.04)	(−1.12)	(0.72)
$\overline{r}_{i,t}$	−1.55	−11.44	9.55	−13.42	−2.07	−1.35	−0.40	−4.59
	(−1.15)	(−1.85)	(1.72)	(−1.68)	(−1.46)	(−0.20)	(−0.06)	(−0.54)
Fund fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.5, cont.

Panel B: Multivariate regressions

	Weight type							
	Call	Put	Net	Gross	Call	Put	Net	Gross
Active share	−0.94	4.70	−5.57	3.49	0.21	−1.95	2.08	−1.14
	(−1.84)	(2.52)	(−3.35)	(1.51)	(0.20)	(−0.68)	(0.79)	(−0.31)
Beta of stocks	0.02	1.03	−1.01	1.19	−0.07	0.48	−0.55	0.48
	(0.33)	(2.62)	(−2.60)	(2.63)	(−0.83)	(1.54)	(−1.85)	(1.30)
Liquidity	−0.26	−0.47	0.29	−1.02	−0.17	−0.23	0.11	−0.53
	(−2.65)	(−1.16)	(0.80)	(−1.84)	(−2.62)	(−0.62)	(0.32)	(−1.33)
Log(fund size)	−0.07	−0.12	0.05	−0.31	−0.05	−0.25	0.21	−0.36
	(−2.81)	(−1.03)	(0.46)	(−2.06)	(−1.08)	(−1.71)	(1.47)	(−2.08)
Mean stake	−0.53	−10.54	10.31	−11.43	−0.47	−0.33	−0.93	−0.55
	(−0.50)	(−1.70)	(1.75)	(−1.59)	(−0.24)	(−0.03)	(−0.09)	(−0.05)
Turnover	0.64	2.74	−2.11	3.43	0.28	0.37	−0.13	0.79
	(3.25)	(3.52)	(−2.94)	(3.38)	(1.75)	(0.66)	(−0.23)	(1.19)
Fund fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18,456	18,456	18,456	18,456	18,456	18,456	18,456	18,456
R^2	0.02	0.03	0.03	0.04	0.24	0.41	0.37	0.43

Panel C: Risk Shifting Incentives

	Weight type			
	Call	Put	Net	Gross
$r_{i,t}^{\mathrm{YTD}} * \mathrm{Dummy}_{\mathrm{March}}$	0.43	2.34	−1.86	3.37
	(0.89)	(1.11)	(−0.86)	(1.94)
$r_{i,t}^{\mathrm{YTD}} * \mathrm{Dummy}_{\mathrm{June}}$	0.32	0.77	−0.25	1.45
	(0.60)	(0.31)	(−0.10)	(0.56)
$r_{i,t}^{\mathrm{YTD}} * \mathrm{Dummy}_{\mathrm{September}}$	0.76	0.80	−0.25	2.71
	(1.57)	(0.35)	(−0.11)	(1.10)
$r_{i,t}^{\mathrm{YTD}} * \mathrm{Dummy}_{\mathrm{December}}$	−0.94	6.93	−7.61	4.65
	(−1.25)	(1.98)	(−1.99)	(1.19)
Fund fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	19,209	19,209	19,209	19,209
R^2	0.237	0.396	0.363	0.422

Table 2.6: Contemporaneous Option Weight Changes, Market Returns, and VIX

This table presents estimates of γ in the one of the following univariate regressions:

$$\omega_t - \omega_{t-1} = \gamma r_{m,t} + \epsilon_t$$
$$\omega_t - \omega_{t-1} = \gamma(VIX_t - VIX_{t-1}) + \epsilon_t$$

where $r_{m,t}$ is market return; ω_t is equal-weighted or value-weighted mean across funds of one of the following: call weight, put weight, or their net and gross values. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. *Weight Change* columns report estimates from the regression displayed above, while *Weight Level* columns report estimates from regressions on weight level instead of weight change. All coefficients are multiplied by 100. Newey-West with 3 lags t-statistics are reported in parentheses. The sample period is 2005–2014.

	Aggregate		Average Fund	
Weight Type	Weight Change	Weight Level	Weight Change	Weight Level
		Market Return		
call	−0.38	0.31	0.28	0.72
	(−1.33)	(0.67)	(0.75)	(1.38)
put	−0.84	0.43	−0.55	2.81
	(−1.10)	(0.41)	(−0.94)	(2.44)
net	0.46	−0.11	0.84	−2.09
	(0.56)	(−0.12)	(0.92)	(−2.05)
gross	−1.22	0.74	−0.27	3.53
	(−1.48)	(0.56)	(−0.71)	(2.40)
		VIX Change		
call	0.30	0.14	−0.38	−0.35
	(0.67)	(0.38)	(−0.89)	(−1.29)
put	0.96	−0.26	0.54	−1.34
	(1.05)	(−0.27)	(0.76)	(−0.92)
net	−0.66	0.40	−0.92	0.99
	(−0.68)	(0.44)	(−0.86)	(0.72)
gross	1.26	−0.12	0.16	−1.68
	(1.19)	(−0.11)	(0.35)	(−1.08)

Table 2.7: Aggregate and Average Market Timing

The table presents the market timing estimates for all funds in aggregate and for the average fund. Market timing measures are estimated as γ in the one of the following regressions:

$$
\begin{aligned}
r_{m,t+1} &= \gamma(\omega_t - \omega_{t-1}) + \alpha + \epsilon_t \\
VIX_{t+1} - VIX_t &= \gamma(\omega_t - \omega_{t-1}) + \alpha + \epsilon_t
\end{aligned}
$$

where $r_{m,t+1}$ is market return; ω_t is equal-weighted or value-weighted mean across funds of one of the following: call weight, put weight, or their net and gross values. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. *Weight Change* columns report estimates from the regression displayed above, while *Weight Level* columns report estimates from regressions on weight level instead of weight change. The sample period is 2005–2014.

	Aggregate		Average Fund	
Weight Type	Weight Change	Weight Level	Weight Change	Weight Level
		Market Return		
call	−3.87	3.95	−9.34	2.39
	(−0.84)	(0.94)	(−1.45)	(0.56)
put	−9.28**	1.60	−0.21	2.56*
	(−3.15)	(0.78)	(−0.06)	(1.72)
net	4.43*	−0.93	−1.23	−3.60*
	(1.78)	(−0.38)	(−0.49)	(−1.94)
gross	−8.17**	1.44	−3.47	1.75
	(−3.29)	(0.93)	(−0.90)	(1.49)
		VIX Change		
call	3.12	−1.00	10.09	0.13
	(0.70)	(−0.24)	(1.64)	(0.03)
put	3.49	−1.71	−0.73	−1.46
	(1.10)	(−0.87)	(−0.23)	(−0.99)
net	−1.15	2.08	1.88	2.36
	(−0.46)	(0.89)	(0.78)	(1.29)
gross	3.69	−1.11	2.47	−0.88
	(1.39)	(−0.74)	(0.67)	(−0.76)

Table 2.8: Macro Funds Subsample: Aggregate and Average Market Timing

The table presents the market timing estimates for the sample of hedge funds following the Global Macro strategy. Market timing measures are estimated as γ in the one of the following regressions:

$$\begin{aligned} r_{m,t+1} &= \gamma(\omega_t - \omega_{t-1}) + \alpha + \epsilon_t \\ VIX_{t+1} - VIX_t &= \gamma(\omega_t - \omega_{t-1}) + \alpha + \epsilon_t \end{aligned}$$

where $r_{m,t+1}$ is market return; ω_t is equal-weighted or value-weighted mean across funds of one of the following: call weight, put weight, or their net and gross values. Market options weight in a fund portfolio is calculated as the underlying value of these options divided the total assets of the hedge fund firm including assets that are not reported in 13F filings. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. *Weight Change* columns report estimates from the regression displayed above, while *Weight Level* columns report estimates from regressions on weight level instead of weight change. The sample period is 2005–2014.

	Aggregate		Average Fund	
Weight Type	Weight Change	Weight Level	Weight Change	Weight Level
		Market Return		
call	−23.58*	−12.71	−1.55**	−0.69
	(−1.73)	(−0.99)	(−2.45)	(−0.90)
put	−12.97	3.97	−1.44**	0.05
	(−1.24)	(0.44)	(−2.29)	(0.07)
net	−0.33	−18.83	−0.04	−0.99
	(−0.03)	(−1.59)	(−0.08)	(−1.12)
gross	−11.66	−0.89	−1.22**	−0.19
	(−1.71)	(−0.15)	(−3.19)	(−0.45)
		VIX Change		
call	24.49*	19.83*	2.21**	1.33*
	(1.88)	(1.65)	(4.10)	(1.86)
put	9.99	2.04	1.46**	0.14
	(0.99)	(0.24)	(2.44)	(0.19)
net	4.32	14.05	0.45	1.57*
	(0.40)	(1.21)	(0.87)	(1.91)
gross	10.56	4.78	1.49**	0.44
	(1.60)	(0.87)	(4.51)	(1.09)

Table 2.9: Cross-Section of Market Timing, Weight Changes

The table presents percentiles of the cross-sectional distribution of market timing. Market timing is measured by the coefficient γ_i in the following two regressions, which are estimated separately

$$\begin{aligned} r_{m,t+1} &= \gamma_i(\omega_{i,t} - \omega_{i,t-1}) + \alpha_i + \epsilon_{i,t} \\ VIX_{t+1} - VIX_t &= \gamma_i(\omega_{i,t} - \omega_{i,t-1}) + \alpha_i + \epsilon_{i,t} \end{aligned}$$

where $r_{m,t+1}$ is market return; $\omega_{i,t}$ denotes one of the following: call weight, put weight, or their net and gross values. In parentheses are percentiles of the cross-sectional distribution of market timing T-statistics. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. The sample period is 2005–2014.

	Percentile						
Weight type	5	10	20	50	80	90	95
				Market return			
call	−1.19	−0.38	−0.03	0.00	0.05	0.51	2.04
	(−2.15)	(−1.66)	(−0.83)	(0.04)	(0.69)	(1.11)	(1.43)
put	−1.39	−0.71	−0.18	0.00	0.22	0.56	1.33
	(−1.67)	(−1.24)	(−0.67)	(−0.01)	(0.70)	(1.09)	(1.45)
net	−1.35	−0.54	−0.21	0.00	0.17	0.57	1.37
	(−1.53)	(−1.18)	(−0.76)	(−0.03)	(0.61)	(1.21)	(1.63)
gross	−1.31	−0.58	−0.18	0.00	0.20	0.47	1.24
	(−1.66)	(−1.31)	(−0.68)	(−0.03)	(0.71)	(1.06)	(1.32)
				VIX change			
call	−1.95	−0.74	−0.09	0.00	0.00	0.28	1.32
	(−1.98)	(−1.50)	(−0.80)	(−0.14)	(0.58)	(1.73)	(3.28)
put	−2.09	−0.58	−0.23	0.00	0.23	0.99	2.39
	(−1.67)	(−1.35)	(−0.83)	(−0.11)	(0.62)	(1.63)	(2.32)
net	−2.34	−0.78	−0.23	0.00	0.20	0.50	2.09
	(−2.35)	(−1.57)	(−0.56)	(0.09)	(0.80)	(1.37)	(1.91)
gross	−1.45	−0.44	−0.22	0.00	0.18	0.84	2.34
	(−1.70)	(−1.35)	(−0.81)	(−0.11)	(0.69)	(1.88)	(2.64)

Table 2.10: Cross-Section of Market Timing, Weight Levels

The table presents percentiles of the cross-sectional distribution of market timing. Market timing is measured by the coefficient γ_i in the following two regressions, which are estimated separately

$$\begin{aligned} r_{m,t+1} &= \gamma_i \omega_{i,t} + \alpha_i + \epsilon_{i,t} \\ VIX_{t+1} - VIX_t &= \gamma_i \omega_{i,t} + \alpha_i + \epsilon_{i,t} \end{aligned}$$

where $r_{m,t+1}$ is market return; $\omega_{i,t}$ denotes one of the following: call weight, put weight, or their net and gross values. In parentheses are percentiles of the cross-sectional distribution of market timing T-statistics. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. The sample period is 2005–2014.

	Percentile						
Weight type	5	10	20	50	80	90	95
	Market return						
call	−2.03	−0.34	0.00	0.00	0.16	0.98	3.74
	(−2.50)	(−1.42)	(−0.73)	(0.29)	(1.03)	(1.35)	(1.69)
put	−1.89	−0.70	−0.08	0.03	0.48	1.02	3.86
	(−2.05)	(−1.29)	(−0.50)	(0.38)	(1.04)	(1.40)	(1.70)
net	−2.55	−0.95	−0.41	−0.01	0.14	0.70	2.14
	(−1.81)	(−1.42)	(−1.04)	(−0.28)	(0.48)	(1.29)	(2.02)
gross	−1.89	−0.60	−0.10	0.02	0.39	0.88	2.34
	(−2.26)	(−1.36)	(−0.59)	(0.36)	(1.04)	(1.46)	(1.84)
	VIX change						
call	−2.52	−0.58	−0.08	0.00	0.00	0.36	1.39
	(−2.38)	(−1.37)	(−0.76)	(−0.10)	(0.48)	(1.08)	(2.50)
put	−2.21	−1.02	−0.24	0.00	0.17	0.86	3.18
	(−2.06)	(−1.53)	(−0.85)	(−0.09)	(0.51)	(1.26)	(2.51)
net	−2.90	−0.68	−0.16	0.00	0.20	0.97	2.13
	(−2.36)	(−1.52)	(−0.53)	(0.09)	(0.75)	(1.52)	(2.05)
gross	−2.04	−0.70	−0.22	0.00	0.16	0.73	2.84
	(−2.10)	(−1.56)	(−0.94)	(−0.08)	(0.55)	(1.52)	(2.52)

Table 2.11: Bootstrapped P-Values of Market Timing T-Statistics, with Weight Changes

The table presents the cross-sectional percentiles of market timing T-statistics and their bootstrapped one-sided p-values. The T-statistics correspond to the estimates of γ_i in the one of the following regressions:

$$\begin{aligned} r_{m,t+1} &= \gamma_i(\omega_{i,t} - \omega_{i,t-1}) + \alpha_i + \epsilon_{i,t} \\ VIX_{t+1} - VIX_t &= \gamma_i(\omega_{i,t} - \omega_{i,t-1}) + \alpha_i + \epsilon_{i,t} \end{aligned}$$

where $r_{m,t+1}$ is market return; $\omega_{i,t}$ denotes one of the following: call weight, put weight, or their net and gross values. The table presents left p-values for the 50th and lower percentiles and right p-values for higher percentiles. The bootstrapping procedure involves 1000 random permutations of the time-series of market returns and VIX, while the panel of option weights remains unchanged from its empirical value. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. The sample period is 2005–2014.

	Percentile						
Weight type	5	10	20	50	80	90	95
				Market return			
call	−2.15	−1.66	−0.83	0.04	0.69	1.11	1.43
	(0.16)	(0.08)	(0.48)	(0.63)	(0.81)	(0.85)	(0.87)
put	−1.67	−1.24	−0.67	−0.01	0.70	1.09	1.45
	(0.64)	(0.66)	(0.89)	(0.44)	(0.83)	(0.90)	(0.89)
net	−1.53	−1.18	−0.76	−0.03	0.61	1.21	1.63
	(0.85)	(0.79)	(0.72)	(0.36)	(0.97)	(0.75)	(0.71)
gross	−1.66	−1.31	−0.68	−0.03	0.71	1.06	1.32
	(0.68)	(0.53)	(0.90)	(0.35)	(0.85)	(0.94)	(0.98)
				VIX change			
call	−1.98	−1.50	−0.80	−0.14**	0.58	1.73	3.28**
	(0.37)	(0.26)	(0.28)	(0.02)	(0.71)	(0.07)	(0.01)
put	−1.67	−1.35	−0.83	−0.11	0.62	1.63	2.32
	(0.71)	(0.44)	(0.28)	(0.10)	(0.76)	(0.08)	(0.07)
net	−2.35**	−1.57	−0.56	0.09	0.80	1.37	1.91
	(0.05)	(0.11)	(0.89)	(0.90)	(0.32)	(0.39)	(0.37)
gross	−1.70	−1.35	−0.81	−0.11	0.69	1.88**	2.64**
	(0.68)	(0.43)	(0.31)	(0.08)	(0.61)	(0.01)	(0.01)

Table 2.12: Bootstrapped P-Values of Market Timing T-Statistics, with Weight Levels

The table presents the cross-sectional percentiles of market timing T-statistics and their bootstrapped one-sided p-values. The T-statistics correspond to the estimates of γ_i in the one of the following regressions:

$$\begin{aligned} r_{m,t+1} &= \gamma_i \omega_{i,t} + \alpha_i + \epsilon_{i,t} \\ VIX_{t+1} - VIX_t &= \gamma_i \omega_{i,t} + \alpha_i + \epsilon_{i,t} \end{aligned}$$

where $r_{m,t+1}$ is market return; $\omega_{i,t}$ denotes one of the following: call weight, put weight, or their net and gross values. The table presents left p-values for the 50th and lower percentiles and right p-values for higher percentiles. The bootstrapping procedure involves 1000 random permutations of the time-series of market returns and VIX, while the panel of option weights remains unchanged from its empirical value. Market options weight in a fund portfolio is calculated as the underlying value of these options divided by the underlying value of the fund portfolio, which is calculated as the value of stocks and the underlying value of options. Market options are options on S&P 500 ETF (ticker SPY). The weight is winsorized at 1% level across the full sample. The sample period is 2005–2014.

	Percentile						
Weight type	5	10	20	50	80	90	95
				Market return			
call	−2.50	−1.42	−0.73	0.29	1.03	1.35	1.69
	(0.12)	(0.58)	(0.51)	(0.90)	(0.14)	(0.19)	(0.12)
put	−2.05	−1.29	−0.50	0.38	1.04	1.40	1.70
	(0.36)	(0.69)	(0.94)	(0.98)	(0.13)	(0.16)	(0.18)
net	−1.81	−1.42	−1.04	−0.28**	0.48	1.29	2.02
	(0.11)	(0.16)	(0.09)	(0.03)	(0.99)	(0.66)	(0.27)
gross	−2.26	−1.36	−0.59	0.36	1.04	1.46*	1.84*
	(0.16)	(0.58)	(0.84)	(0.97)	(0.13)	(0.10)	(0.06)
				VIX change			
call	−2.38*	−1.37	−0.76	−0.10	0.48	1.08	2.50
	(0.10)	(0.22)	(0.20)	(0.20)	(0.62)	(0.60)	(0.20)
put	−2.06	−1.53	−0.85	−0.09	0.51	1.26	2.51*
	(0.21)	(0.11)	(0.20)	(0.28)	(0.75)	(0.53)	(0.08)
net	−2.36	−1.52	−0.53	0.09	0.75	1.52	2.05
	(0.11)	(0.19)	(0.76)	(0.82)	(0.31)	(0.11)	(0.21)
gross	−2.10	−1.56	−0.94	−0.08	0.55	1.52	2.52*
	(0.15)	(0.11)	(0.11)	(0.34)	(0.66)	(0.24)	(0.08)

Table 2.13: Market Timing of the Average Fund

The table presents pooled means of market timing measures. Market timing is first calculated for each fund-quarter observation over the first month following the quarter-end, and then a pooled equal-weighted mean is calculated over fund-quarter observations. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. Market option weight in a fund portfolio, calculated separately for each call and put and for each underlying market ETF, is calculated as the derivative value of the options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. Timing is presented in units of *percent per month*. *T-pooled* column presents pooled t-statistics and *T-FM* column presents Fama-MacBeth t-statistics. *Option Users* columns present results for the sample of funds that held market options in at least one quarter; *Heavy Option Users* columns present results for the sample of funds that in at least 10 quarters held market options with the value of the underlying of at least 10% of the value of the total fund portfolio. The sample period is 2005–2014.

	Option Users			Heavy Option Users		
Timing Measure	Mean	T-pooled	T-FM	Mean	T-pooled	T-FM
$\overline{\omega_t r_t}$	-0.10	-2.23	-1.36	-0.32	-4.28	-2.18
$\overline{\omega_t(r_t - \bar{r})}$	-0.05	-1.20	-0.79	-0.16	-2.25	-1.19
$\overline{\omega_t(r_t - \overline{r_m})}$	-0.10	-2.33	-1.42	-0.34	-4.44	-2.26
$\overline{\omega_t(r_t - r_m)}$	-0.11	-2.33	-1.41	-0.35	-4.55	-2.27
$\overline{\omega_t(r_t - \overline{\beta_A r_m})}$	-0.04	-0.91	-0.65	-0.16	-2.19	-1.14
$\overline{\omega_t(r_t - \beta_A r_m)}$	0.01	0.61	0.08	-0.01	-0.17	-0.06
$\overline{\omega_t(r_t - \overline{\beta_D r_m})}$	0.08	1.70	1.00	0.17	2.28	1.56
$\overline{\omega_t(r_t - \beta_D r_m)}$	0.19	4.72	1.31	0.55	4.20	1.33

Table 2.14: Cross-Section of Market Timing

The table presents percentiles of the cross-sectional distribution of market timing. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. Market option weight in a fund portfolio, calculated separately for each call and put and for each underlying market ETF, is calculated as the derivative value of the options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. The unit of measurement is percent per month. In parentheses are percentiles of the cross-sectional distribution of market timing T-statistics. Funds with less than 10 quarters of non-zero market option holdings are excluded. The sample period is 2005–2014.

	Percentile										
Timing Measure	1	5	10	20	30	50	70	80	90	95	99
$\overline{\omega_t r_t}$	−2.77	−1.28	−0.80	−0.38	−0.19	−0.08	−0.02	0.00	0.02	0.19	2.08
	(−4.17)	(−3.33)	(−2.87)	(−2.26)	(−1.99)	(−1.40)	(−0.73)	(−0.15)	(0.39)	(0.72)	(0.97)
$\overline{\omega_t(r_t - \bar{r})}$	−2.22	−0.81	−0.52	−0.23	−0.11	−0.04	−0.01	0.01	0.04	0.10	2.28
	(−3.46)	(−2.53)	(−2.18)	(−1.95)	(−1.54)	(−1.01)	(−0.25)	(0.16)	(0.54)	(0.97)	(1.27)
$\overline{\omega_t(r_t - \overline{r_m})}$	−2.87	−1.29	−0.81	−0.39	−0.19	−0.09	−0.02	0.00	0.02	0.19	2.06
	(−4.18)	(−3.35)	(−2.90)	(−2.28)	(−2.02)	(−1.42)	(−0.79)	(−0.22)	(0.38)	(0.69)	(0.95)
$\overline{\omega_t(r_t - r_m)}$	−2.92	−1.28	−0.81	−0.40	−0.19	−0.09	−0.02	0.00	0.02	0.19	2.10
	(−4.15)	(−3.34)	(−2.85)	(−2.25)	(−2.01)	(−1.41)	(−0.78)	(−0.27)	(0.31)	(0.70)	(0.95)
$\overline{\omega_t(r_t - \overline{\beta_A r_m})}$	−2.00	−0.89	−0.58	−0.24	−0.10	−0.03	0.00	0.02	0.07	0.18	2.43
	(−3.22)	(−2.45)	(−2.19)	(−1.81)	(−1.56)	(−1.00)	(−0.11)	(0.32)	(0.79)	(0.96)	(1.17)
$\overline{\omega_t(r_t - \beta_A r_m)}$	−1.34	−0.54	−0.26	−0.08	−0.03	0.00	0.02	0.04	0.20	0.53	2.46
	(−2.77)	(−2.15)	(−1.83)	(−1.30)	(−0.99)	(−0.09)	(0.48)	(0.77)	(0.96)	(1.05)	(1.56)
$\overline{\omega_t(r_t - \overline{\beta_D r_m})}$	−1.09	−0.28	−0.10	−0.03	−0.01	0.01	0.07	0.15	0.44	0.79	2.92
	(−2.62)	(−1.95)	(−1.53)	(−1.07)	(−0.49)	(0.48)	(1.02)	(1.27)	(1.56)	(1.85)	(2.69)
$\overline{\omega_t(r_t - \beta_D r_m)}$	−0.89	−0.27	−0.06	0.00	0.01	0.06	0.20	0.46	1.03	1.85	4.05
	(−1.39)	(−0.85)	(−0.67)	(−0.19)	(0.24)	(0.73)	(1.02)	(1.21)	(1.36)	(1.47)	(1.72)

Table 2.15: Bootstrapped P-values of Cross-Sectional Percentiles

The table presents cross-sectional percentiles of market timing T-statistics and their bootstrapped left p-values in parentheses. The bootstrapping method involves resampling without replacement with 1000 samples. Market returns are resampled while market option holdings remain fixed at their empirical values. Funds with less than 10 quarters of non-zero market option holdings are excluded. Market options are options on broad market index ETFs identified by the following tickers: SPY, QQQQ, IWM, IVV, IWN, DIA, MDY. Market option weight in a fund portfolio, calculated separately for each call and put and for each underlying market ETF, is calculated as the derivative value of the options divided by the derivative value of the fund portfolio, which is calculated as the value of stocks and the derivative value of options. The sample period is 2005–2014.

	Percentile										
Timing Measure	1	5	10	20	30	50	70	80	90	95	99
$\overline{\omega_t r_t}$	−4.17	−3.33	−2.87	−2.26	−1.99	−1.40	−0.73	−0.15	0.39	0.72	0.97
	(0.11)	(0.08)	(0.08)	(0.11)	(0.07)	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)	(0.02)
$\overline{\omega_t(r_t - \bar{r})}$	−3.46	−2.53	−2.18	−1.95	−1.54	−1.01	−0.25	0.16	0.54	0.97	1.27
	(0.06)	(0.11)	(0.10)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.29)	(0.33)
$\overline{\omega_t(r_t - \overline{r_m})}$	−4.18	−3.35	−2.90	−2.28	−2.02	−1.42	−0.79	−0.22	0.38	0.69	0.95
	(0.12)	(0.08)	(0.08)	(0.11)	(0.06)	(0.06)	(0.04)	(0.06)	(0.06)	(0.05)	(0.02)
$\overline{\omega_t(r_t - r_m)}$	−4.15	−3.34	−2.85	−2.25	−2.01	−1.41	−0.78	−0.27	0.31	0.70	0.95
	(0.11)	(0.08)	(0.09)	(0.12)	(0.06)	(0.05)	(0.04)	(0.05)	(0.02)	(0.06)	(0.02)
$\overline{\omega_t(r_t - \overline{\beta_A r_m})}$	−3.22	−2.45	−2.19	−1.81	−1.56	−1.00	−0.11	0.32	0.79	0.96	1.17
	(0.19)	(0.22)	(0.13)	(0.08)	(0.04)	(0.04)	(0.07)	(0.08)	(0.19)	(0.14)	(0.04)
$\overline{\omega_t(r_t - \beta_A r_m)}$	−2.77	−2.15	−1.83	−1.30	−0.99	−0.09	0.48	0.77	0.96	1.05	1.56
	(0.15)	(0.20)	(0.20)	(0.25)	(0.27)	(0.52)	(0.56)	(0.61)	(0.29)	(0.06)	(0.31)
$\overline{\omega_t(r_t - \overline{\beta_D r_m})}$	−2.62	−1.95	−1.53	−1.07	−0.49	0.48	1.02	1.27	1.56	1.85	2.69
	(0.23)	(0.10)	(0.08)	(0.04)	(0.08)	(0.20)	(0.44)	(0.56)	(0.57)	(0.62)	(0.69)
$\overline{\omega_t(r_t - \beta_D r_m)}$	−1.39	−0.85	−0.67	−0.19	0.24	0.73	1.02	1.21	1.36	1.47	1.72
	(0.88)	(0.96)	(0.81)	(0.71)	(0.77)	(0.77)	(0.71)	(0.72)	(0.56)	(0.36)	(0.19)

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