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Three Essays on Hedge Fund Investments and Investment Banks

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THREE ESSAYS ON
HEDGE FUND INVESTMENTS AND INVESTMENT BANKS

A Dissertation Presented

by

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DEDICATION

To my parents and my husband.

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ABSTRACT

THREE ESSAYS ON
HEDGE FUND INVESTMENTS AND INVESTMENT BANKS

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This dissertation focuses on studying how investment banks affect hedge fund equity investments through acting as prime brokers for hedge funds. The first chapter studies how the relationships between hedge funds and investment banks are maintained through equity issuance and prime brokerage business. Using a comprehensive dataset of hedge funds and IPO allocations, I examine IPO allocation decisions by investment banks to hedge funds. I find that investment banks whose prime brokers have strong relationships with hedge funds and are lead underwriters of IPOs tend to allocate more IPOs to these hedge funds. Moreover, the allocation to hedge funds is larger when IPOs are underpriced, and the allocations are larger during bearish periods compared to bullish periods. I further document that hedge fund investments in IPOs are determined by the strength of hedge fund-prime broker relationships, rather than by hedge fund manager skills. I also find that hedge funds which have multiple prime brokers tend to invest in more IPOs. As a result, prime brokers implicitly support hedge funds through favorable IPO allocations.

The second chapter finds that hedge funds can profit from anticipating upcoming changes in analysts' recommendations before they become public. I provide evidence supporting the hypothesis that hedge funds that have prime brokerage affiliations with analysts' investment banks have access to information on upcoming analysts' recommendations. Focusing on recommendations issued up to two days following stock holding report date, I find that large hedge funds that are clients of the investment bank (affiliated hedge funds) tend to buy upgrades and sell downgrades in a larger magnitude compared to other hedge funds before the public release of recommendations. Moreover, relative to non-affiliated hedge funds, affiliated hedge funds have a higher probability to trade in a way that is consistent with upcoming recommendation changes and earn higher (or avoid lower) short-term abnormal returns by buying (or selling) before upgrades (or downgrades). The results indicate that prime brokerage affiliation is an important source of private information on analysts' reports for hedge funds.

The third chapter studies hedge funds' equity investment strategies by examining the investment value and risk consequence of their holdings concentration in large-cap and small-cap stocks. We find that stocks, especially small-cap ones, with concentrated hedge fund holdings earn higher future returns than those with less concentrated holdings. We also find that stocks with concentrated hedge fund holdings have higher downside risks, and the holdings concentration expedites the drop of stock performance, especially during financial crisis. In addition, small-cap stocks with higher holdings concentration are associated with hedge funds using higher leverage, consistent with Stein (2009) that deleverage leads to the negative return shock and downside risks in stocks. Our findings suggest that hedge fund managers are skilled in making equity investment under different market efficiency.

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CHAPTER 1

HEDGE FUNDS AND PRIME BROKERS: FAVORABLE IPO ALLOCATIONS

1.1 Introduction

The recent literature concentrated on the relationship between investment banks and hedge funds. Hedge funds are very important clients for investment banks. [1] Hedge funds rely on prime brokerage services provided by investment banks and produce significant revenues for investment banks through a variety of services, such as securities lending, margin financing, and settlement facilities. As a result, prime brokers aggressively compete among each other to secure hedge funds' business. A central question is whether the incentives to initiate or maintain the prime brokerage business relationships drives investment banks to favor their hedge fund clients by providing them with profitable investment opportunities. Prime brokers are incentivized to favor their hedge fund clients in order to obtain and keep their lucrative business. In this paper we study evidence of such favoritism and identify the channel through which prime brokers favor their hedge fund clients.

In this paper, we examine how the relationships between hedge funds and investment banks are maintained through equity issuance and prime brokerage businesses. Specifically, we test the favoritism of Initial Public Offerings (IPOs) allocation by asking whether investment banks reward their associated prime brokerage business clients by allocating underpriced IPOs underwritten by them and whether the investment decisions in IPOs are determined by hedge funds' relationships with investment banks or by the managers' skills.

[1] "Investment Banks Are Too Dependent on Hedge Funds", Bloomberg News, 23 March 2005, sec. FP, FP13. Moreover, according to Greenwich Associates, Wall Street collects \$33 million a year in trading commissions from the average hedge fund versus \$16 million from the average mutual fund.

The topic of allocation of IPOs to institutional investors has long interested researchers. It is well documented that IPO underwriters play a central role in determining the allocation of IPO shares among different investors. Traditional bookbuilding theory of IPO underpricing (e.g., Benveniste and Spindt (1989)) predicts that the lead underwriters will allocate underpriced shares to induce investors to truthfully reveal private information on demand for the IPO, and investors will help investment banks price and ultimately reduce IPO underpricing for the issuer. In contrast, the recent agency-based explanation of IPO allocations argues that lead underwriters have strong incentives to allocate "hot" issues that are expected to trade up strongly in the aftermarket to their favored institutional clientele, possibly in exchange for inflated brokerage commissions in subsequent trades or additional investment banking businesses (e.g., Loughran and Ritter (2002), Reuter (2006)). Although the two views are different in their underlying motives, they both predict that particular groups of investors will be favored in allocating underpriced issues. Binay, Gatchev, and Pirinsky (2007) find that, consistent with the bookbuilding theory of IPOs, underwriters favor institutional investors they have previously worked with in allocating underpriced IPOs. Reuter (2006) documents a positive correlation between brokerage commissions that mutual fund families paid for trade execution and the number of underpriced shares allocated by the lead underwriters, providing support for the agency-based explanation.

Hedge funds are reported as the fastest growing contingent of the major IPO investor types in the US IPO market. According to a survey by PwC 2016[2], the participation of hedge funds in US IPOs has been increasing at a rate of 3% per year since 2013 and reached 24% in 2015. Despite the popularity of the allocation favoritism, however, little empirical evidence has been provided on its efficiency as a mechanism for hedge fund investments in IPOs, especially on how connections between hedge funds and investment banks are set up to achieve the favoritism.

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[2]See "Considering an IPO? A continuing series Insight into the mindset of institutional IPO investors in the US", PwC, May 2016.

In this paper, we empirically study these connections through prime brokerage businesses offered by investment banks to hedge funds. Act as intermediaries between hedge funds and investment banks, prime brokers offer a bundle of basic services to hedge funds including clearance, custody, securities lending, and financing (see Bryce (2008)), and earn a large amount of revenue for investment banks by charging fees on financing and earning brokerage commissions due to the frequent trading of hedge funds[3]. Given the enormous profits, prime brokers compete for their customers by expanding their services and maintaining their relationships with hedge funds through ancillary services such as IPO allocation, capital introduction, advising, consulting, and technical support. According to the theoretical literature of IPO allocation, underwriters may favor their connected hedge fund customers, and the quid pro quo for such favorable treatment is the growing prime brokerage business relationship or the information on IPO demand provided by such connected hedge funds.

We contribute to the literature by identifying the channel through which prime brokers tend to favor hedge fund clients. First, we identify investment banks which are lead underwriters of IPOs. We then study whether hedge funds with prime brokerage business relationships in these investment banks (i.e., relationship hedge funds) are more likely to invest in these IPOs compared to hedge funds without such relationships (i.e., non-relationship hedge funds). We expect that these relationships lead to a higher likelihood of hedge fund investments in IPOs under favoritism. Second, we study whether investment banks tend to allocate "hot" and underpriced IPOs to their clients compared to non-relationship hedge funds. Given the favoritism mechanism, investment banks would like to allocate more shares of underpriced issues to relationship hedge funds in order to attract more prime brokerage businesses and earn higher brokerage fees. On the other hand, as quid pro quo for their private information on demand for issues, hedge funds might be allocated "hotter" IPOs, which

[3]According to "Unsettled on Wall Street Institutional Investor Magazine, 14 October 2003 and "Hey Big Spender, Analysts on Call International Herald Tribune, 6 March 2007, Hedge fund trading volume accounts for 40 to 50 percent of the daily trading volume in US stock markets (Cox, 2006).

would reward hedge funds with higher returns. An interesting hypothesis we are able to test here is regarding the prime brokerage relationship based allocation in "hot" and "cold" IPOs. Specifically, we study whether prime brokers play an important role in supporting relationship hedge fund investments in "hot" issues. Finally, using hedge fund data, we are able to empirically examine whether hedge fund IPO investments are determined solely by the investment banks or in part by fund manager skill. Would the hedge funds' own characteristics affect their investments in "hot" and "cold" IPOs? Answering the above questions allows us to identify the function of prime brokers from the perspectives of both hedge funds and investment banks.

To address the above issues, we organize our empirical analysis into two parts. First, we study the pattern of IPO allocation to hedge funds from issuer-underwriter level analysis. We empirically test the *relationship hypothesis* discussed earlier that hedge funds having prime brokerage relationships with lead underwriters of an IPO are more likely to invest in that IPO than are hedge funds without these relationships. Here we test prime allocation, which is the propensity of allocating IPOs to relationship hedge funds, in terms of the IPO underpricing, pre-market demand, issue size, lead underwriter reputation and other IPO characteristics. Second, we use prime broker-fund relationships and funds' own characteristics to analyze hedge fund investments in IPOs. We examine relationship and non-relationship hedge fund positions in "hot" and "cold" IPOs, respectively. We test the determinants of hedge fund investments in IPOs including manager's alpha, using multiple and reputed prime brokers, and other funds' own characteristics.

We use quarterly equity holdings disclosed in 13F filings with the SEC to infer the IPO shares allocated to hedge fund companies as data on IPO allocations is not publicly available. Our sample includes a universe of 215 hedge fund management companies with 135 prime brokers and 2,638 IPOs with 468 lead underwriters, spanning the period from 1994 through 2012. With this dataset, we are able to identify hedge funds with or without prime brokerage relationships with lead underwriters of the owned IPOs. Further, in order to infer the IPO allocations to hedge funds, we separate IPOs into "hot" and "cold" IPOs using zero initial IPO return as a cutoff. The categorized sample allows us to analyze the hedge fund investments separately.

We present a number of results on IPO allocations and hedge fund investments. In the first part of our analysis, using issue-level data, we document the pattern of IPO allocations by exploring the measure and the cross-sectional determinants of prime allocation. We find that investment banks are more likely to allocate issues underwritten by them to their hedge fund clients who have prime brokerage relationships with them. We further find that the average prime allocation is not stationary over years, and it is more than 10 times higher in the bearish period (2001-2003 and 2008-2009) than in bullish period. We interpret this result as evidence that hedge funds request more favoritism in market downturns, and that investment banks play an important role in helping relationship hedge funds or hedge funds they previously worked with to get through the hard times. Our results suggest that prime brokerage business relationships with lead underwriters increase the chances for relationship hedge funds to access IPOs that are more underpriced and with higher demand revealed during the book-building process - a result consistent with bookbuilding theory of IPO allocations. The higher prime allocation to lower equity holdings relationship hedge funds again provides evidence of the supportive role of prime brokers in hedge fund investments.

Our analysis of prime allocation provides considerable support for the relationship hypothesis that hedge funds having prime brokerage relationships with the lead underwriters of an IPO are more likely to invest in that IPO than are hedge funds without these relationships. In particular, our results support the favoritism that investment banks reward their prime brokerage business relationship clients with profitable investment opportunities – preferential access to "hot" IPOs, especially in market downturns.

In the second part of our analysis, using fund-level data, we separately study hedge fund companies' investments in IPOs owned by relationship (non-relationship) hedge funds and in "hot" ("cold") IPOs, relative to their asset under management. We document that hedge fund investments in IPOs are determined by their business relationships with investment banks, rather than by fund managers' skills. According to the agency-based explanation of IPO allocation, lead underwriters will use allocations of underpriced IPOs to reward investors with which they have strong business relationships. Therefore, I include three proxies for the closeness and strength of the relationships between hedge funds and lead underwriters: multiple connections to prime brokers, the use of influential prime brokers, and the participation in "hot" issues. We find that the use of multiple or top prime brokers leads to more investments in IPOs owned by relationship hedge funds, but less in IPOs owned by non-relationship hedge funds, and the relationship hedge funds put more investments in IPOs than non-relationship hedge funds if a large number of "hot" issues are allocated to the fund company. We further find that hedge fund companies have more investments in "hot" issues if they have more prime broker-lead underwriter relationships, use a single prime broker, or connect to smaller prime brokers. Our results suggest a resource dilution or rebalance effect that the use of multiple or bigger prime brokers leads to the dilution of valuable resources assigned to each individual hedge funds.

In our analysis, we also document that younger hedge funds invest more in "hot" issues, and the relationship hedge funds with smaller lagged returns make more investments in IPOs. Our results suggest that investment banks tend to support the start-up hedge funds or poorly-performed hedge funds by providing them with more profitable investment opportunities. Indirectly, the favorite allocations increase hedge fund investors' confidence, and thus more capital flows are introduced into hedge funds, which further suggests the incubative role of prime brokers in helping hedge funds grow.

The remainder of this paper is organized as follows. Section 1.2 briefly reviews the related literature. Section 1.3 describes our sample and presents summary statistics. Section 1.4 defines our measure of favoritism, and analyzes the determinants of favorite IPO allocations. Section 1.5 presents our results on relationship and non-relationship hedge fund investments in IPOs, and the capital introduction through IPO allocations. Section 1.6 concludes.

1.2 Related literature

Our paper relates to two strands of literature. First, prime brokers have played an important role in the emerging literature on relating hedge fund investments to investment banks. Chuang and Teo (2012) show that, in order to earn commissions and fees from their associated hedge fund clients, sell-side analysts tend to craft favorable reports for stocks purchased by hedge funds who are the prime brokerage clients of their investment banks. It argues that the analysts do not want to go against the investment view of their associated hedge fund clients, and thus are optimistic about the stocks held by those hedge funds. Klaus and Rzepkowski (2009) find that hedge funds using multiple prime brokers had a better performance than those relying on a single prime broker. The competitions between multiple prime brokers drive down the credit line and improve the margin, reducing the funding risks faced by hedge funds.

Our paper is most closely related to Qian and Zhong (2014) that study the hedge funds possession of private information through post-IPO stock abnormal returns. They show that the connections between prime brokers and IPO underwriters are important sources of private information for hedge funds. Different than their paper, our paper uses initial IPO returns and fund returns to evaluate the effect of prime broker-lead underwriter relationships on hedge fund investments in IPOs. Two other closely related papers are Goldie (2011) and Chuang and Kang (2014) who also study the information provision role of prime brokers from the relationships between hedge funds and investment banks. Goldie (2011) finds that risk arbitrage hedge funds are more likely to invest in mergers and acquisitions (M&A) when hedge funds' prime brokers also work as advisors in the deals and that hedge funds outperform naive portfolios of risk arbitrage investment by gaining information advantages through their connections with investment banks. Chuang and Kang (2014) examine the comovement of hedge fund returns using common information hypothesis, which suggests that the strong comovement in the returns of hedge funds is induced by the valuable information provided by the prime brokers.

Our paper speaks to the relationship analysis based on the role of prime brokers, but we explore the advantages of using relationships from a different angle. Our analysis suggests that prime brokers support the investments and the growths of hedge funds directly through favorable IPO allocations, rather than indirectly through information provision. Moreover, our results supplement the existing literature on the ancillary services such as capital introduction provided by prime brokers.

A second strand of literature is the favoritism of IPO allocations to institutional investors. As the traditional theoretical paradigm, bookbuilding theory by Benveniste and Spindt (1989) argues that lead underwriters allocate underpriced IPOs to reward regular investors for truthfully revealing private information on share values of IPOs, or for accepting allocations in overpriced IPOs. In contrast, agency-based explanation of IPO allocations by Loughran and Ritter (2002) and Reuter (2006) suggests that lead underwriters favor the institutional investors who have strong business relationships with them by allocating underpriced IPOs to those investors. Although the bookbuilding theory and agency-based explanation predict the allocation of IPOs under different motivations of underwriters, they are not mutually exclusive. The predictions of IPO allocations to particular groups by the two views are consistent the notion of favoritism of the underwriters. For example, Reuter (2006) exemplifies the favoritism of lead underwriters in the context of mutual funds, and finds a positive correlation between yearly brokerage commissions paid by the funds to lead underwriters and the IPOs participation of mutual fund families. His findings suggest that business relationships with lead underwriters increase mutual funds' access to underpriced IPOs. Binay, Gatchev, and Pirinsky (2007) suggests that, as a favor, institutional investors with past IPO participation with the lead underwriter are more likely to be allocated underpriced IPOs than those without the past IPO participation relationships, as regular investors help underwriters lower expected underpricing by providing information on demand for IPOs.

Our paper adds to the current IPO allocation favoritism literature that we document a robust positive relationship between IPOs underpricing and the propensity of allocating IPOs to hedge funds with prime brokerage relationships with the lead underwriters. We do not argue over the efficiency of the two views, as either one does not appear to completely explain the entire relationship and non-relationship allocation differential (e.g., Aggarwal, Prabhala, and Puri (2002)). We contribute to the IPO literature through developing evidence on how connections are set up to achieve favorable allocations. In addition, different than other IPO literature, our analysis of favoritism are not limited to the issuer-underwriter level, but rather we use underwriter-investor relationships and investors characteristics to predict the favorite allocations.

1.3 Data and sample characteristics

We compile a comprehensive dataset of hedge fund IPO ownership by extensively matching data from hedge fund databases, 13F filings, and Securities data Companies (SDC). Our final sample includes a universe of 215 hedge fund management companies with the associated 3,300 individual hedge funds and 135 prime brokers, and 2,638 IPOs held by hedge funds with the associated 468 lead underwriters, spanning the period from 1994 through 2012.

1.3.1 Construction of the sample

We identify IPOs offered between Jan 1994 and Dec 2012 from the Securities Data Company's (SDC) New Issues database excluding American Depository Receipts, unit offerings, closed-end funds, real estate investment trusts (REITs). We also exclude IPOs with offer prices less than $5, and IPOs missing the first six days of information from the Center for Research in Security Prices (CRSP), leaving 5,241 IPOs in our sample. We obtain IPO related data including the offer price, initial price range, first-day closing price, shares, underwriter syndicate (including the lead underwriters), and SIC code from SDC database. We use CRSP to fill in any missing first-day closing prices.

Due to the lack of IPO allocation data, we construct proxies for IPO allocations using equity holdings of hedge funds from the same period. The hedge fund holdings data are based on institutional holdings from 13F filings to Securities and Exchange Commission (SEC). We separate hedge funds holdings from other institutional holdings by matching hedge fund companies in hedge fund databases with those in 13F ownership databases.

We use information from TASS database to identify all hedge funds and hedge fund management companies. The hedge fund databases provide information on monthly hedge fund returns, on asset under management (thereafter, AUM), net asset values (thereafter, NAV), and other fund characteristics. As a private investment company, hedge funds are not required to register with the SEC, but those with more than $100 million under management must report their holdings to the SEC each quarter on form 13F, including all long positions (but no short position) in U.S. stocks and a few other securities greater than 10,000 shares or $200,000 in the market value. Holdings are reported at the management company level at the end of each calendar quarter.

Following the methodology of Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we compile a list hedge fund management companies from TASS hedge fund databases, and match them with the companies registered as investment advisers from 13F database. We discard some companies whose hedge fund assets only make a small part of their aggregated institutional portfolio. Since the name of a hedge fund company may not be the same in different databases, we manually check unmatched investment advisers through online searching to determine if they are hedge fund companies. We find records for 520 hedge fund companies.

For each of the 520 companies, we check whether the firm is a registered investment adviser with the SEC. We include a firm in our sample if it is not registered, since registration is a prerequisite for conducting non-hedge fund business such as advising mutual funds and pension plans. If the firm is registered, we obtain its ADV form and check its eligibility for our sample based on two criteria: (1) at least 50% of its clients are "Other pooled investment vehicles (e.g., hedge funds)" or "High net worth individuals," and (2) it charges a performance fee for its advisory services. This process leaves us with 380 companies and 25,633 total stock holdings.

To identify hedge funds holdings in long positions, we focus solely on hedge funds using long/short equity hedge, equity market neutral, and event driven strategies. To mitigate a potential survivorship bias, we used both "Live" and "Graveyard" funds starting in 1994. If a fund has missing asset under management, we quarterly interpolate the missing observations using adjacent quarterly assets under management. We omit observations where no asset under management was reported at the beginning or the end of the fund time series. We also eliminate hedge funds having fewer than 24 months of observations. We winsorize fund flows at top and bottom 1%. AUM and NAV are converted to US dollars if the original currency is not US dollar. The monthly exchange rates of US dollar are downloaded from Bloomberg.

After these filtering procedures, 215 hedge fund management companies with the managed 3,300 individual hedge funds, and 2,638 IPOs with the associated 468 lead underwriters are identified in our compiled databases.

To connect prime brokers to hedge funds IPOs investment, we incorporate information on prime broker(s) that a hedge fund is associated with from the TASS hedge fund database. Different than hedge fund holdings, prime brokers are identified at the fund level in these databases, and a hedge fund may be associated with one or more prime brokers. Since a management company often offers multiple hedge funds, we use all listed prime brokers within the same institution for a hedge fund company.

Over the past ten years, the prime brokerage industry has been dominated by top investment banks. In the snapshot of TASS data in September 2012, there are 465 global prime brokers, with top 10 biggest brokers account for about 85% of the market share in the global hedge funds business. The ten major prime brokers ranked according to their market share in our sample, were, respectively, Goldman Sachs, Credit Suisse, Morgan Stanley, JP Morgan, UBS, Deutsche Bank, Citi, Barclays, Bank of America Merrill Lynch, and Newedge.[4]

In our unreported summary statistics of filtered TASS database, there are 1,220 hedge fund companies and 343 prime brokers. The prime brokers are reported by 49% of hedge funds, among which about 17% declare to have multiple prime brokers. In our sample, we excluded funds that did not report information on their prime brokers.

To check the bias caused by the dynamics of the relationships between hedge funds and prime brokers, we examine the prime broker turnover using yearly snapshots of the TASS database from 2006 to 2012. We measure the changes of prime brokers for each hedge fund company and the changes of multiple prime brokers each calendar year. Similar to Goldie (2011), we do not find significant turnover of prime brokers. The stable relationships between hedge funds and prime brokers would not bias the results in this paper.

1.3.2 Summary statistics

Table 1.1 reports the fund characteristics at the company-level for the full sample from TASS hedge fund database matched with 13F institutional holding data and SDC issue data from 1994 through 2012. The characteristics include the number of hedge funds per company, the number of prime brokers per company, the average alpha of the hedge funds per company, the number of hedge funds with positive alpha per company, and the basic company-level fund characteristics including AUM (in $ million), return, flow, age, and standard deviation of return. In our sample, there are 216 hedge fund companies that manage 3,300 individual hedge funds using long/short equity hedge, equity market neutral, or event driven strategies. The average number of prime brokers used per company is 1.7, and 43% of the sample use at least one prime brokers. From the compiled database, the average number of IPOs owned a company is 8, which is only 0.7 percent of the average stocks held by each company.

[4]It is in accordance with the Wilson (2012), which covers more than $1.6 trillion of asset under management of hedge funds.

For a hedge fund company in each quarter, the alpha is estimated as the risk-adjusted return by regressing the net-of-fee monthly excess return on the seven factors constructed by Fung and Hsieh (2004). We elaborate the details of estimating alpha in section 4.2. In Table 1.1, the mean of average alpha of the managed hedge funds per company is -0.08 and the median is -0.024, suggesting that more than half of hedge funds have negative alpha, and the distribution of alpha is skewed to the left. The statistics of other company-level characteristics are estimated according to the measurement in section 4.1. The mean of the CAUM, CReturn, and CFlow for each company is 212 ($ million), 0.025, and 24.8, respectively.

Table 1.2 reports the summary statistics of the IPO sample based on the merged TASS, SDC data, and 13F institutional holding data. The total number of IPO is 5,241 from 1994 to 2012, and 2,638 of these IPOs have hedge fund ownership at the end of the quarter in which IPO takes place. The reported statistics in Panel A include the number of IPOs, offer price, shares offered ($ million), initial IPO return, offer proceeds, and pre-IPO demand. The mean initial IPO return, which is the day one return of IPO measured from the offer price to the first-day closing price, is 26% in our sample. We partition IPOs owned by hedge funds into hot versus cold IPOs using zero initial return as a cutoff, and the average initial return for hot and cold IPOs is 36% and -0.05%, respectively. We examine hot versus cold IPOs for most of our results throughout this paper. As expected, offer proceeds from hot IPOs are higher than cold IPOs. The pre-IPO demand, calculated as the percentage difference between the midpoint of the filing price range and the offer price, is 0.05 on average, and the pre-IPO demand for hot IPOs is more than double as high as for cold IPOs.

Table 1.2 Panel B presents summary statistics of the IPO allocations on the company level for the identified hedge funds. The reported statistics in Panel B include the number of hedge fund companies, the number of IPOs allocated to each fund company, the allocation frequency, the fraction of allocation, and the allocation value. The allocation frequency is calculated as the ratio of the number of IPOs allocated to a fund company and the number of IPOs offered in each quarter. The fraction of allocation is calculated as the ratio of shares allocated to a fund company and the shares offered in each quarter. The allocation value is the average value of a fund company's investment, calculated as shares allocated to hedge funds times offer price. We report the statistics of hot IPOs and cold IPOs, respectively. In our sample, there are on average 306 hot IPOs allocated to a fund company, compare to 231 cold IPOs received by the fund company. Moreover, the allocation frequency in hot IPOs is 18, whereas it is 11 in cold IPOs. In particular, the fraction of allocation of hot IPOs is 12.64%, which is twice as much as that of cold IPOs. Our results suggest that there are more hot IPOs than cold IPOs in our sample, and the chance of getting allocations of hot IPOs is higher that of cold IPOs.

1.4 Prime brokers and IPOs allocation

In this section, we quantitatively measure the role that prime brokers played in allocating IPOs to hedge funds. We then proceed to examine the determinants of propensity of allocating IPOs to hedge funds with prime brokerage relationships with lead underwriters.

1.4.1 The measurement of IPOs allocation propensity

One of the main questions we address is whether hedge funds who have prime brokerage relationships with the lead underwriters in an IPO are more likely to invest in that IPO. As discussed above, in order to reward existing hedge funds customers and attract more prime brokerage businesses, investment banks have incentives to increase the probability of IPOs allocation to their high net-worth investors. In our analysis, following Binay, Gatchev, and Pirinsky (2007), we quantify the role of prime brokers by measuring the propensity that hedge funds are allocated an IPO conditional on their prime brokerage businesses relationships with the lead underwriters of that IPO, compared to hedge funds without those relationships. We focus on lead underwriters because they are most important in making IPO allocation decisions.

For each IPO i in quarter t, we define the prime allocation ($\Delta P_{i,t}$) as the difference between the probability that hedge funds get an allocation ($A_{i,t}$) of IPO i conditional on their prime broker-lead underwriter relationships ($R_{i,t}$) and the unconditional allocation probability:[5]

$$\Delta P_{i,t} = P(A_{i,t}|R_{i,t}) - P(A_{i,t}) \tag{1.1}$$

Where

$$P(\cdot|*) = \frac{\sum_{j=1}^{n^*_{i,t}} \text{ HF investment}_{j,i,t}}{\sum_{i=1}^{N^*_t}\sum_{j=1}^{n^*_{i,t}} \text{ HF investment}_{j,i,t}}$$

A HF $\text{investment}_{j,i,t}$ is defined as the dollar value of IPO i owned by hedge fund company j at quarter t, which is equal to the offer price times the holding shares of the hedge fund company.[6] $n^*_{i,t}$ and N^*_t are, respectively, the number of hedge fund companies invested in IPO i in quarter t and the number of IPOs in quarter t, conditional (or unconditional) on that the hedge fund companies have prime brokerage relationships with the lead underwriter(s) of IPO i.

We calculate the conditional probability of IPO allocation to hedge funds $P(\cdot|*)$ as the sum of hedge fund companies' investments in quarter t in IPO i whose lead underwriter(s) also provides prime brokerage services to the hedge funds listed in the companies, divided by the sum of hedge fund companies' investments in quarter t in all IPOs that are underwritten by the same lead underwriter(s). The unconditional probability is the investments in IPO i in quarter t of hedge fund companies divided by the sum of hedge fund companies' investments in all IPOs in the same quarter. We exclude the hedge funds that do not have any prime broker-lead underwriter relationship.

The prime allocation explains the probability that an IPO is allocated to relationship hedge funds in excess of the probability of allocating the IPO to all hedge funds. We expect

[5]Instead of unconditional probability $P(A_{i,t})$, we also use non-conditional probability $P(A_{i,t}|\neg R_{i,t})$ as the second term in measuring prime allocation . We obtain similar results in unreported tests.

[6]We get similar empirical results when we use the number of IPOs held by hedge fund company as $A_{i,t}$.

that the prime allocation is positive since the relationship hedge funds are expected to get more allocations of IPOs, according to our relationship hypothesis.

Table 1.3 Panel A shows the statistical analysis for the propensity of allocating IPOs to relationship hedge funds. We estimate the allocation probability for totally 2,638 IPOs with the average initial return 26.72% in our sample. The average probability of allocation IPOs to hedge funds conditional on their prime brokerage relationships with the lead underwriters of the IPOs is 31.12%, which is much higher than the average unconditional probability of IPO allocation 7.91%. These results lead to a significantly positive allocation propensity 23.21%, providing a strong evidence of the favoritism of investment banks. That is, investment banks are more likely to favor their hedge fund clients who have prime broker-lead underwriter relationships by allocating IPOs underwritten by them, indicating the supportive roles of prime brokers in initiating and maintaining business relationships between hedge funds and investment banks.

To evaluate the impact of IPO underpricing on the allocation propensity, we examine the likelihood that the relationship hedge funds participate in IPOs with two different levels of underpricing. We partition IPOs into hot and cold IPOs based on the zero initial IPO return, and estimate the conditional allocation, unconditional allocation, and prime allocation in each underpricing categories.

In Table 1.3 Panel A, we report the statistical analysis for hot and cold IPOs, as well as aggregate statistics for all IPOs. The allocations in two underpricing categories are much higher than the corresponding non-relationship allocations, leading to the significantly positive prime allocation in two categories. The propensity of allocating hot IPOs to relationship hedge funds (24.73%) is significantly higher than the propensity of allocating cold IPOs to them (17.60%). We test for the differences in the prime allocation between hot and cold IPOs. The p-value from this test strongly rejects the null that the propensities of allocating IPOs to relationship hedge funds are the same for hot and cold IPOs.

Our statistical analysis provides evidence that, consistent with our relationship hypothesis, hedge funds with prime brokerage business relationships with the lead underwriters of an IPO are more likely to participate in the IPO than hedge funds without those relationships, and investment banks are more inclined to allocate underpriced issues to favor their hedge fund clients who request prime brokerage services from them.

To examine the evolution of the favoritism, we plot the yearly average prime allocations of IPOs to relationship hedge funds from 1994-2012 in Figure 1.2. In order to control for the market impact on IPO issuance, we standardize the average prime allocations by dividing it by the ratio of the number of IPOs in year t and the number of IPOs over all years. The average favoring behavior is not stationary over the time period. The likelihood of the excess allocation tends to increase sharply in bearish period, and gradually goes back to normal as the markets recover. From early 2000 to technical wreck (09/00-09/02), the prime allocation increased by 32.45% as US economy transits from good to bad, and reached the highest point 35% in 2001. In 2008-2009, hedge funds with prime brokerage business relationships with the lead underwriters of an IPO are about 26% more likely to participate in that IPO than the non-relationship hedge funds. Moreover, in 2008, the likelihood of allocating hot IPOs to relationship hedge funds is 14% more than that of allocating cold IPOs to them. In contrast, the likelihood of excess allocation to relationship hedge funds in bull market is relatively stable.

We also provide statistical analyses of prime allocation over different time periods in Table 1.3 Panel B. We divide our sample into five subperiods, among which 2001-2003 and 2008-2009 are bearish periods, and the rest time periods are bullish periods. Consistent with the above analyses, the average prime allocation in each subperiod is positive, with the highest value 37.56% in 2008-2009. Further, the allocation propensity of hot IPOs is significantly higher than that of cold IPOs in all bearish periods. However, it is not necessarily the case in bullish periods. In 2004-2007, the average prime allocation of hot IPOs is significantly lower than that of cold IPOs, suggesting that relationship hedge funds may sometimes act as dumping grounds of IPO allocations for the investment banks' benefits[7].

A potential interpretation is that hedge funds request more favoritism in bear market than in bull market. According to Brunnermeier and Pedersen (2008), in market downturn, the low market liquidity increases the risks of financing a trade, thus increasing margins and restricting hedge funds from providing market liquidity. Hedge funds facing the increasing funding risks look for profitable investment opportunities from their prime brokers. Moreover, in the post-crisis period, there are much less IPOs issued, but firms going public in this period are significantly larger in terms of size and sales volume (see Henry and Gregorious (2013)). A direct implication is that relationship hedge funds have a higher chance of receiving IPO shares of high quality firms when IPOs supply is low. In order to help hedge funds get through the crisis and stabilize the market, investment banks tend to allocate their prime brokerage clients more underpriced IPOs. Our sample statistics shows that hedge fund investments in hot IPOs contribute more to the increased prime allocations in 2008-2009 bear market than to those in 2001-2003 bear market. A possible reason is that hedge funds using long/short equity hedge and equity market neutral are affected little by the market downturn in 2001-2003, making the favorable allocation less necessary. Our results are also in accordance with Benveniste and Spindt (1989) and Bakke, Leite, and Thorburn (2011) that underwriters compensate investors by underpricing the issue more for truthfully revealing positive private information in bear market than in bull market.

Alternatively, would it be possible that hedge funds' past participation in IPOs leads to the high prime allocation? As a reward for past participation, lead underwriters may allocate more issues to their regular relationship hedge fund clients, especially in bear market when favoritism is especially needed. Following Binay, Gatchev, and Pirinsky (2007), we measure

[7] Mooney (2013) finds that IPOs purchased by affiliated mutual funds have lower mean initial returns than others, suggesting that investment banks may allocated cold IPOs to affiliated mutual funds to preserve investment banking fee income at the expense of fund shareholders.

the past relationship participation in each IPO which examines the likelihood that a hedge fund participate in an IPO underwritten by the same lead investment bank within five years of the current IPO. Our unreported results show that the average past relationship participation is 27.12 percent and the highly positive excess probability indicates that hedge funds with stronger past IPO business relationships with the lead underwriter are more likely to participate in current IPO. Compare to non-relationship hedge funds, hedge funds with prime broker relationships are 7.35 percent more likely to have past IPO business participation. More important, similar to prime allocations to relationship hedge funds, the past relationship participation also shows stronger likelihood of IPO allocation to hedge funds in bear market. The statistical results provide an alternative interpretation that past relationship IPO business participation can at least partly account for the pattern of prime allocations in bearish periods.

1.4.2 Determinants of the prime allocation

To further examine whether investment banks favor the relationship hedge funds to a greater extent than non-relationship hedge funds, we perform a multivariate regression of the prime allocation (ΔP) on a variety of variables potentially related to IPOs allocation.

$$\begin{aligned}\Delta P = \alpha &+ \beta_1 \textit{Initial IPO Return} + \beta_2 \textit{Pre-IPO Demand} + \beta_3 \textit{Log(Issuer Assets)} \\ &+ \beta_4 \textit{Log(Proceeds)} + \beta_5 \textit{Log(HF Size)} + \beta_6 \textit{Past Relation} + \beta_7 \textit{Reputation} \\ &+ \beta_8 \textit{Lead UW Size} + \beta_9 \textit{HighTech} + \beta_{10} \textit{VC Backed} \end{aligned} \tag{1.2}$$

Table 1.4 reports results on the regression analysis of the IPO allocation to relationship and non-relationship hedge funds for the entire samples, as well as samples in bullish and bearish periods. The definitions of the determinants are as follows. *Initial IPO Return* is the day one return of the IPO, measured from the offer price to the first-day closing price. *Pre-IPO Demand* is the percentage difference between the midpoint of the filing range and the offer price. *Log(Issuer Assets)* is the natural logarithm of the firm's total assets before the offering. *Log(Proceeds)* is the natural logarithm of the IPO offer proceeds. *Log(HF Size)* is the natural logarithm of the average equity holdings of the hedge fund companies participated in the IPO. *Past Relation* is the average historical relationship participation for the lead underwriter's IPOs over the past five years (see Binay, Gatchev, and Pirinsky (2007)). *Reputation* is the lead underwriter reputation ranking obtained from Jay Ritter's web site (see Loughran and Ritter (2004)). *Lead UW Size* is the number of lead underwriters of the IPO. *HighTech* equals one if the IPO firm is in high-tech and Internet IPOs (see Ljungqvist and Wilhelm (2003) and Loughran and Ritter (2004)), and zero otherwise. *VC Backed* equals one if the IPO has venture capital backing, and zero otherwise.

IPO underpricing and pre-market demand measures are highly correlated, but the offer price does not fully adjusted to reflect pre-market interest in the book-building process (see Benveniste and Spindt (1998) and Hanley (1993)). We include *Initial IPO Return* and *Pre-IPO Demand* in our regression separately. The coefficients on these two variables in both models are positive and significant, suggesting that the hotter the issue, the higher the chance that investment banks allocate the issue underwritten by them to their hedge fund clients who have prime brokerage relationship with them. Consistent with earlier univariate statistics, these results suggest that investment banks tend to favor their relationship hedge funds by providing them more profitable investment opportunities.

Table 1.4 also shows that lead underwriters reward the prime brokerage relationship hedge funds by allocating them issues of bigger firms, according to the positive and significant coefficients on *Log(Issuer Asset)*. These results support the favoritism of the underwriters to hedge funds since bigger firms are generally considered to have more stock market liquidity. The coefficients on *Log(Proceeds)* in both models are positive and significant, suggesting positive connections between IPO allocation and issue size. The coefficients on average hedge funds equity holdings are negative and significant for prime allocation, indicating that the lower equity holdings are associated with the higher probability of allocating IPOs to relationship hedge funds. This provides evidence that investment banks are more likely to favor start-up or young in equity investment relationship hedge funds, suggesting the supportive role of prime brokers in hedge fund growth.

In our regression, *Past Relation* is included to control for the past IPO business participation. The regression coefficients on *Past Relation* in all models are positive and significant, suggesting that relationship hedge funds are more likely to be allocated current IPOs if they also have past IPO business relationship with the lead underwriter.

Relationship hedge funds also have higher chance of being allocated issues with more lead underwriters and issues underwritten by reputed lead investment banks. This situation can arise because more reputable investment have wider access to hedge funds, and the IPO participation is consequently higher for relationship hedge funds connected to those investment banks. The coefficients on Internet and technology IPOs and VC-backed IPOs, however, are not significant. We also control for the quarter and the industry of the IPO by including time and industry fixed effects, and the F-statistics are significant for all models.

1.5 Prime brokers and hedge fund investments in IPOs

Our results in previous section suggest that lead investment banks are more inclined to allocate IPOs to hedge funds having prime brokerage relationships with them, and the role of prime brokers are analyzed using IPO characteristics. In this section, we use hedge fund characteristics to study how the hedge fund investment decisions in IPOs are affected by prime brokers and the fund itself. We separately analyze the determinants of hedge fund companies' investments in IPOs owned by relationship (or, non-relationship) hedge funds and in hot (or, cold) IPOs. We also study how the hedge fund investor flows are affected after IPO allocations.

1.5.1 Relationship hedge fund investments in IPOs

A concern we address in this section is whether the prime brokers would affect hedge fund investments in IPOs, and in particular, whether hedge funds with prime brokerage relationship with the lead underwriters of the owned IPOs tend to make IPO investment decisions differently, compared to non-relationship hedge funds. In our analysis, we test whether this process relies in part on using multiple prime brokers and big prime brokers[8], and on receiving allocations from friendly lead underwriters, after controlling for funds own characteristics.

For comparison purposes, we run a pooled regression of the company's IPO investments by relationship and non-relationship hedge funds, respectively, as a fraction of the company's AUM on the characteristics of prime brokers and hedge funds. The regression has the following specification:

$$IA_{i,t} = \alpha + \beta_1 MultiPBs_{i,t} + \beta_2 BigPBs_{i,t} + \beta_3 HotIPOs_{i,t} + \beta_5 Controls_{i,t-1} + \epsilon_{i,t} \quad (1.3)$$

where $IA_{i,t}$ is IPO investments by relationship (or, non-relationship) hedge funds measured by the percentage of AUM of company i in quarter t, $MultiPBs_{i,t}$ is a dummy variable indicating whether the fund company i has more than one prime brokers in quarter t, $BigPBs_{i,t}$ is the number of top ten prime brokers of the fund company i in quarter t, $HotIPOs_{i,t}$ is the number of hot IPOs participated in by the fund company i in quarter t. $MultiPBs_{i,t}$, $BigPBs_{i,t}$, and $HotIPOs_{i,t}$ indicate the closeness in the relationships between hedge funds and lead underwriters. The control variables include the funds' return, flow, age, and standard deviation.

Since the IPO holdings data is company-based, we upgrade fund-level characteristics to the company-level to satisfy the consistency requirements. We first calculate a hedge fund company i's asset under management ($CAUM_{i,t-1}$) and net asset value ($CNAV_{i,t-1}$) as the sum of AUMs and per share sum of AUMs of all hedge funds managed by the company at quarter $t-1$. We then compute the quarterly return ($CReturn_{i,t-1}$) and net money flow

[8]We think the geographical closeness of hedge funds and prime brokers is also an important factor in determining their relationships, but we are not able to include it in our regression due to the data limitations.

($CFlow_{i,t-1}$) for fund company i during quarter $t-1$ as follows:

$$CReturn_{i,t-1} = \frac{CNAV_{i,t-1} - CNAV_{i,t-2}}{CNAV_{i,t-2}} \tag{1.4}$$

$$CFlow_{i,t-1} = \frac{CAUM_{i,t-1} - CAUM_{i,t-2}(1 + CReturn_{i,t-1})}{CAUM_{i,t-2}} \tag{1.5}$$

We also compute the $Age_{i,t-1}$ of the company as the the asset weighted average age of the managed hedge funds and the $CReturnStd_{i,t-1}$ as the standard deviation of the return of the fund company at quarter $t-1$.

Table 1.5 reports the results from the above regression after adjusting standard errors for two-way clustering at the company and quarter level. We include the three characteristic variables separately in our regression to avoid potential correlations. For the relationship hedge funds, the coefficient on the $MultiPBs_{i,t}$ dummy is positive and significant, whereas it is significantly negative for non-relationship hedge funds, suggesting that using multiple prime brokers is associated with higher IPO investments by relationship hedge funds but lower IPO investments by non-relationship hedge funds. We interpret this result as evidence that, for relationship hedge funds, using multiple prime brokers should contribute to more connections between hedge funds and lead underwriters, leading to a higher chance of getting IPO allocations from these relationships. On the other hand, as hedge funds spread balances across multiple prime brokers, the valuable resources from each prime broker are diluted or reduced to a greater extent, compared to those from a exclusively single prime broker. This is especially so for IPO investments by non-relationship hedge funds since their chances of getting IPO allocations are smaller than relationship hedge funds, according to our findings in Section 3.2.

To further test the strength of hedge fund-prime broker relationships, we examine the number of influential prime brokers that a fund company is associated with. Since big prime brokers receive a lion's share of hedge fund business revenue, we expect that they should reward their hedge fund clients by allocating more IPOs. Our test results support this conjecture. The coefficient on $BigPBs_{i,t}$ is positive and significant for relationship hedge funds at 1% level, suggesting that hedge funds tend to make more IPO investments if their prime brokers topped in providing brokerage businesses. Of course, hedge funds without prime broker-lead underwriter relationships cannot get extra rewards for using big prime brokers. The significantly negative coefficient on $BigPBs_{i,t}$ for non-relationship hedge funds is consistent with the dilution effect that using more big prime brokers leads to the less allocations of IPOs.

We also examine the relationship between the ownership of underpriced IPOs and hedge fund investments in IPOs. As expected, the coefficients on $HotIPOs_{i,t}$ for relationship and non-relationship hedge funds are both positive and significant at 1% level, and the relationship hedge funds have more investments in IPOs than non-relationship hedge funds if a large number of hot issues are allocated to the fund company. The results suggest that prime brokerage business relationships facilitate hedge fund investments in IPOs, and a stronger relationship will lead to more profitable investment opportunities.

The coefficient on the lagged return for relationship hedge funds is significant and negative, suggesting that the lower lagged return is associated with the higher investment in IPOs by relationship hedge funds. The coefficients on non-relationship hedge funds, however, are not significant, again proving the favoritism of investment banks on relationship hedge funds. We interpret this as evidence that investment banks help their prime brokerage business clients through hard times by allocating them more IPOs. The roles that prime brokers assume are not limited to the traditional services provider such as clearer or financier, but are extended to facilitator or supporter to the growth of hedge funds.

We also find that the coefficient on the lagged average age of hedge funds is negative and significant for non-relationship hedge funds, but is insignificant for relationship hedge funds. This suggests that lead underwriters tend to allocate more IPOs to younger hedge fund investors, and the connections between prime brokers and lead underwriters balance the age effect and relationship effect out for relationship hedge funds.

We test for the difference in the coefficients on the multiple prime brokers, big prime brokers, and hot IPOs between relationship and non-relationship hedge funds. The p-value from this test strongly rejects the null that the regression coefficients are the same for relationship and non-relationship hedge funds.

1.5.2 Hedge fund investments in hot and cold IPOs

We now examine whether hedge fund investments in IPOs are explained by the relationships between prime brokers and IPO lead underwriters or by the hedge fund alpha. Specifically, we would like to test whether hedge fund investments in IPOs are determined by the allocation decision of investment banks or by the managers' skills. In our analysis, we regress a hedge fund company's investment in hot IPOs and cold IPOs, respectively, as a fraction of company's AUM on the prime broker-lead underwriter relationship and the alpha. The regression has the following specification:

$$\begin{aligned} IA_{i,t} = \alpha &+ \beta_1 Relationship_{i,t} + \beta_2 Alpha_{i,t} + \beta_3 MultiPBs_{i,t} + \beta_4 BigPBs_{i,t} \\ &+ \beta_5 Controls_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{1.6}$$

where $IA_{i,t}$ is hedge fund investments in hot (or, cold) IPOs measured by the percentage of AUM of company i in quarter t, $Relationship_{i,t}$ is a dummy variable indicating whether more than half of the IPOs owned by the fund company i are allocated to the managed relationship hedge funds in quarter t, $Alpha_{i,t}$ is the percentage of positive alpha of the managed hedge funds of company i in quarter t, $MultiPBs_{i,t}$ is a dummy variable indicating whether the fund company i has more than one prime brokers in quarter t, $BigPBs_{i,t}$ is the percentage of top ten prime brokers of the fund company i in quarter t. The definitions of other control variables can be found in section 4.1.

To estimate alpha of individual hedge funds, we adopt a rolling-window method to regress the net-of-fee monthly excess return (in excess of risk-free rate) of each hedge fund on the seven factors constructed by Fung and Hsieh (2004). The seven factors include the S&P 500 monthly return minus risk free rate, Russell 2000 index monthly return minus S&P 500 monthly return, change in the 10-year treasury constant maturity yield, change in the Moody's Baa yield less 10-year treasury constant maturity yield, the return of bond primitive trend-following strategy, the return of currency primitive trend following strategy, and the return of commodity primitive trend-following strategy. Following Naik, Ramadorai, and Stromqvist (2007), for each month, we calculate a funds' factor loadings of the seven factors using the previous 24 months of data, and obtain the risk-adjusted return as the hedge fund alpha. In our sample, 32.75% hedge funds have positive alpha and 67.25% have negative alpha. A fund company's $Alpha_{i,t}$ is calculated as the percentage of positive alphas of the managed hedge funds in the same company.

Table 1.6 reports the results on the regression analysis of hedge fund investments in hot and cold IPOs. The coefficient on $Relationship_{i,t}$ is positive and significant for hot IPO investments, suggesting that the stronger connections bridged by prime brokers between hedge funds and lead underwriters are associated with a significantly higher level of hedge fund investments in hot IPOs. The coefficient on relationship dummy for cold IPO investments is not significant. These results are consistent with the favoritism of investment banks on relationship hedge fund customers. We also test for the differences on $Relationship_{i,t}$ between hot and cold IPO investments. The p-value from this test strongly rejects the null hypothesis that the regression coefficients are the same for hot and cold IPO investments.

As expected, the coefficients on $Alpha_{i,t}$ are not significant for hedge fund investments in both hot and cold IPOs, suggesting that there is no evidence of "hot hand" of hedge fund managers in picking hot IPOs, and it is the underwriter that determines the allocation of IPOs to hedge funds.

In Table 1.6, we examine the effect of hedge fund-prime broker relationship characteristics on hot and cold IPO investment. The coefficients on $MultiPBs_{i,t}$ and $BigPBs_{i,t}$ are negative and significant for hot IPO investments, showing that using multiple prime brokers and using more big prime brokers are associated with less hot IPO allocations. Consistent with the findings in Section 4.1, these results provide evidence of resources rebalancing, that is, as hedge funds spread balances across multiple prime brokers, the valuable resources from each prime broker are diluted or reduced to a greater extent, compared to those from a exclusively single prime broker. In addition, the resources in big prime brokers are not as concentrated as those in small prime brokers, leading to the possible smaller allocations of hot issues to most of their brokerage clients. These coefficients on cold IPO investments are not significant.

The coefficient on the lagged average age of the managed hedge funds is significantly negative for hot IPO investments but is not significant for cold IPO investments, suggesting that younger hedge funds are more likely to be allocated hot IPOs. We interpret these results as evidence of competition between investment banks. In order to attract more prime brokerage or other businesses, lead underwriters allocate more underpriced issues to their new clients, whereas assign more overpriced issues to the aged clients who have already had a stable prime brokerage business relationship with them. Through allocating hot IPOs, investment banks send signals to the start-up hedge funds that they play a role in helping funds formation and expect future cooperation. These findings are also consistent with Liang (1999) that younger funds outperform aged funds in average performance.

To summary, hedge fund investments in IPOs are basically determined by the bank side rather than by the fund manager side. Hedge funds that are younger, with prime brokerage relationship with lead underwriters of the owned IPOs, use single prime broker, or connect to smaller prime brokers are more likely to get allocations of hot IPOs.

1.5.3 Capital introduction through IPOs

So far we have examined the relationship and non-relationship hedge fund investments in hot and cold IPOs. An interesting question is whether the allocation of IPOs helps increasing investors' flow into hedge funds? In other words, would the capital introduction be a side effect of the IPOs allocation?

As prime brokers vie for hedge fund businesses, they seek an edge by helping hedge funds attract new investors. An introduction from a prime broker can help investors identify new managers based on the credit checks performed directly by the lender or the reputations put indirectly behind by the brokerage firm. The connections between hedge funds and prime brokers built through IPO allocations may send a signal to investors that the investments would be beneficial and reliable if more underpriced IPOs are allocated to the funds.

We regress the hedge fund company's flows on the lagged IPO initial return and other lagged fund characteristics. We expect that there are more capital inflows after the allocation of hot IPOs. The regression has the following specification:

$$\begin{aligned} CFlow_{i,t} = \alpha &+ \beta_1 Initial\ IPO\ Return_{i,t-1} + \beta_2 Relationship_{i,t-1} \\ &+ \beta_3 MultiPBs_{i,t} + \beta_4 BigPBs_{i,t} + \beta_5 Controls_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{1.7}$$

where $CFlow_{i,t}$ is measured by the hedge fund company i's net money flows in quarter t. $Initial\ IPO\ Return_{i,t-1}$ is the average initial returns of the IPOs owned by the fund company i at time $t-1$. Definitions of the other variables can be found in section 4.1 and 4.2.

Table 1.7 reports the results on the regression analysis of hedge fund flows on IPO initial returns. The coefficient on $Initial\ IPO\ Return_{i,t-1}$ for net money flows is positive and significant, suggesting that the more investments in the lagged underpriced IPOs are associated with the higher hedge fund inflows. A potential interpretation is that the allocation of hot IPOs increases the investors' confidence on a hedge fund since investment banks tend to reward the client who raises big commission revenue for them through qualified business relationship. The test results support our conjecture that there are more capital inflows after hot IPOs are assigned, providing evidence that the IPOs allocation mechanism contribute to the capital introduction to hedge funds.

We also examine the impact of prime broker characteristics on hedge fund flows. The coefficient on $MultiPBs_t$ is positive and significant, suggesting that using multiple prime brokers is associated with the higher investors' flows. This result is consistent with the role of prime brokers in capital introduction in that the use of multiple prime brokers provides multi-assurance for investors to make investment decisions. The coefficients on the prime broker-lead underwriter relationships and big prime brokers are not significant.

In addition, consistent with hedge fund literature, the coefficient on the lagged hedge fund company's flows is significantly positive, and the coefficient on the average age of the managed hedge funds in the fund company is significant and negative, indicating the investors tend to invest in younger hedge funds.

1.6 Conclusions

In this paper, we use a comprehensive dataset composed of hand-collected data on hedge fund ownership and IPO issuance data from 1994 to 2012 in order to analyze the role of prime brokers in hedge fund investments in IPOs. Our empirical results show that hedge funds having prime brokerage relationships with the lead underwriters of an IPO are more likely to invest in that IPO than are hedge funds without these relationships. Our results support the favoritism in the literature that investment banks reward their business relationship clients with underpriced IPOs.

Benveniste and Spindt (1989) and Reuter (2006) have shown that IPOs are allocated to particular groups of investors under different motivations. Our analyses suggest that, in order to earn inflated brokerage fees, or to attract additional prime brokerage businesses, investment banks reward their hedge fund customers with underpriced issues underwritten by them. The existence and the strength of the hedge funds' business relationships with investment banks will affect the degree of being favored in IPO investments.

Our research adds to the current literature in IPO allocations to hedge funds and in ancillary services provided by prime brokers. In addition to the traditional role of securities lending and margin financing, prime brokers implicitly intermediate the hedge fund investments and introduce capital into hedge funds. Prime brokers show their support to hedge funds through favoring IPO allocations, especially for start-up hedge funds or poorly-performed hedge funds, and in economic downturns. Overall, our results suggest that prime brokers play a supportive role in hedge fund investments and growth, in expectation of stable on-going business relationships with hedge funds.

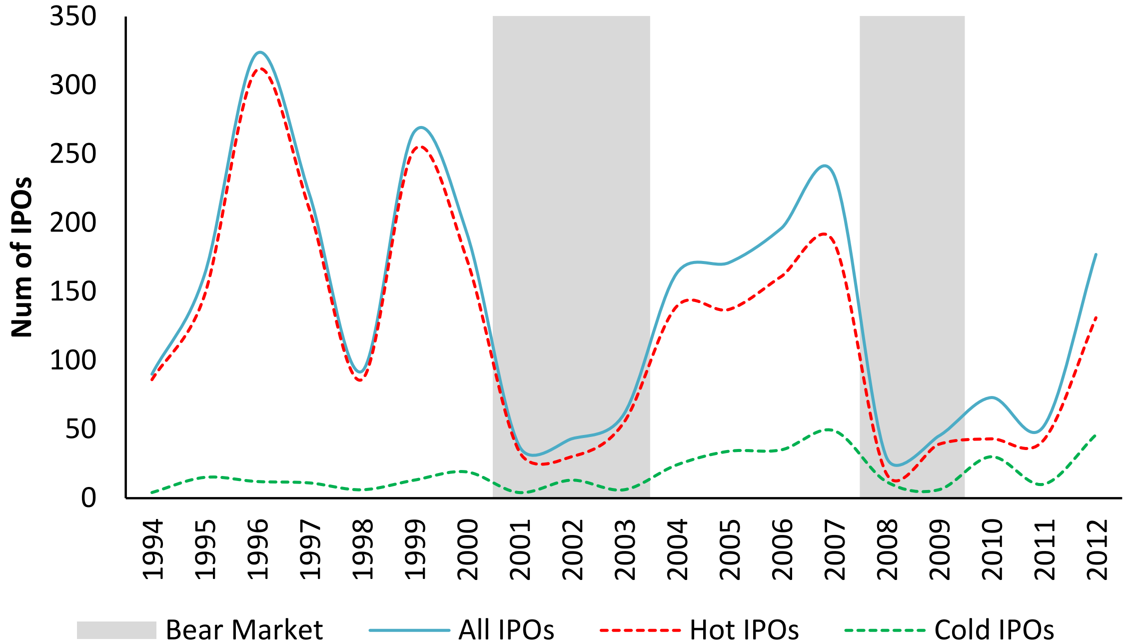


Figure 1.1: The number of IPOs over time

This figure plots the number of all IPOs, as well as the number of hot and cold IPOs. We define issues with initial returns greater than zero as hot IPOs, and as cold IPOs otherwise. The sample period extends from 1994-2012, and the bear markets are from 2001 to 2003 and from 2008 to 2009.

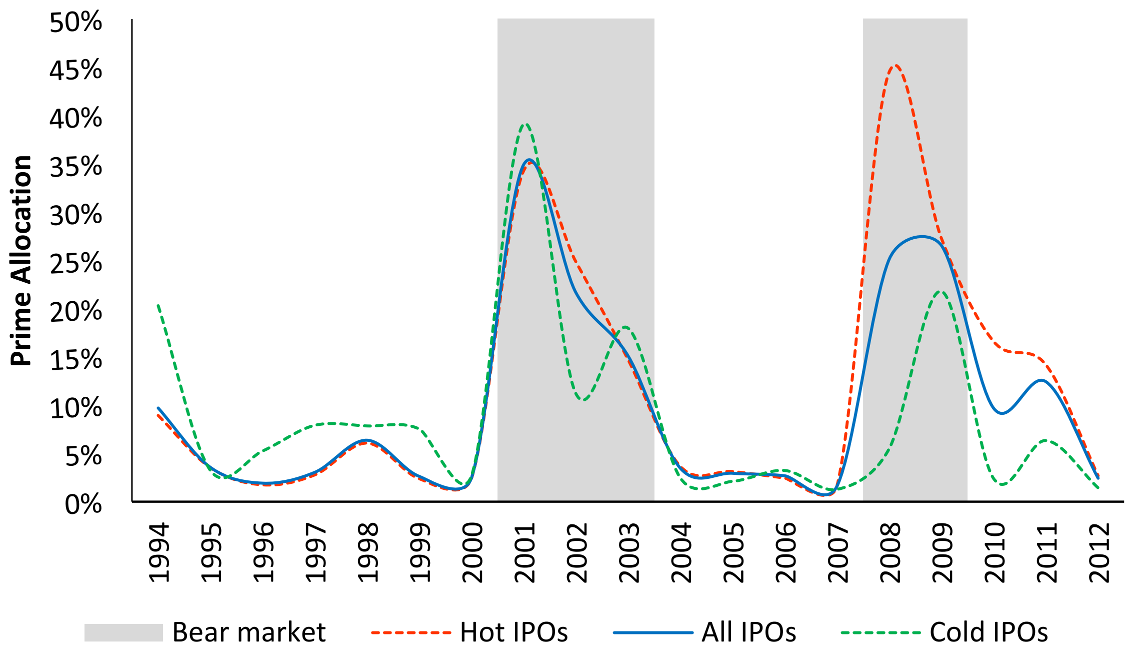


Figure 1.2: The evolution of prime allocations

This figure plots the evolution of average prime allocations of all IPOs, as well as hot and cold IPOs, to relationship hedge funds. We define issues with initial returns greater than zero as hot IPOs, and as cold IPOs otherwise. The sample period extends from 1994-2012, and the bear markets are from 2001 to 2003 and from 2008 to 2009.

Table 1.1: Summary Statistics of Hedge Fund Data

The table presents summary statistics of the time-series average of cross-sectional hedge fund company data in our sample. The source of hedge fund companies are from TASS hedge fund database matched with 13F institutional holding data and SDC issue data from 1994 through 2012. The reported statistics are on the hedge fund company level, including the number of hedge funds per company, the number of prime brokers per company, the number of IPOs owned per company, the average alpha of the hedge funds per company, the number of hedge funds with positive alpha per company, and the basic company-level fund characteristics including CAUM (in $ million), CReturn, CFlow, CAge, and CReturnStd. The reported statistics include mean, standard deviation, the 25th percentile, median, and the 75th percentile.

Number of hedge fund companies	216				
Number of hedge funds	3,300				
Number of prime brokers	135				
	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Number of hedge funds	1.63	1.36	1	1	2
Number of prime brokers	1.7	1	1	1	2
Number of IPOs	8	9	5	1	45
Average alpha	−0.08	6.51	−0.071	−0.024	0.024
Number of HFs with (+)alpha	0.58	0.94	0	0	1
CAUM ($ million)	212	649	13	44	155
CReturn (qtr)	0.025	0.16	−0.018	0.020	0.063
CFlow (qtr)	24.8	4,959	−0.034	0.010	0.11
CAge (qtr)	3.61	1.088	3.05	3.78	4.37
CReturnStd (qtr)	0.066	0.13	0.031	0.040	0.053

Table 1.2: Summary Statistics of IPO Data

The table presents summary statistics of the IPO data in our sample. The source of IPOs are from SDC issue data matched with 13F institutional holding data and TASS hedge fund database from 1994 through 2012. The reported statistics in Panel A include the number of IPOs, offer price, shares offered ($ million), initial IPO return, which is the day one return of the IPO measured from the offer price to the first-day closing price, offer proceeds, and pre-IPO demand, which is the percentage difference between the midpoint of the filing price range and the offer price.
The reported statistics in Panel B include the number of hedge fund companies each quarter, the number of allocation a fund company receives each quarter, the frequency of allocations each quarter, which is calculated as the ratio of the number of IPOs allocated to a fund company and the number of IPOs offered in each quarter, the fraction of allocation a fund company receives each quarter, which is calculated as the ratio of shares allocated to a fund company and the shares offered in each quarter, the allocation value, which is calculated as average value of shares allocated to hedge funds times offer price. We partition IPOs into hot versus cold IPOs using zero initial IPO return as a cutoff.

Panel A: Summary Statistics of IPO Data

Number of IPOs	2,638		
Number of lead managers	468		
	All sample	Hot IPOs	Cold IPOs
Number of IPOs	2,638	2,073	625
Offer price			
Mean	14.63	14.92	13.59
Median	14	14.5	13
Shares offered (million)			
Mean	10.83	10.53	11.90
Median	5	5	5.8
Initial IPO return			
Mean	0.26	0.36	-0.05
Median	0.11	0.17	-0.007
Offer proceeds (million)			
Mean	176.50	246.13	186.22
Median	72	71.60	75.01
Pre-IPO demand			
Mean	0.05	0.08	-0.04
Median	0	0.04	-0.08

Panel B: IPOs allocation on company level

	Hot IPOs	Cold IPOs
Number of HF companies	198	175
Number of IPOs allocated		
mean	306	231
median	249	138
Allocation frequency (qtr)		
mean	18	11
median	11	7
Fraction of allocation (qtr)		
mean	12.64	6.38
median	6	4
Allocation value ($ million) (qtr)		
mean	48.11	42.88
median	17.12	13.25

Table 1.3: Statistical analysis of IPO allocation to relationship hedge funds

This table presents the statistical analysis for the propensity of allocating IPOs to relationship hedge funds. Our sample has 2,638 IPOs from 1994 through 2012 from SDC database. We partition IPOs into hot and cold IPOs based on the zero initial return. The reported statistics include IPO sample size, Initial IPO return, the conditional allocation, which is the probability that hedge funds get an allocation conditional on their prime broker-lead underwriter relationships, the unconditional allocation, which is the probability that the general hedge funds get an allocation of the IPO, and the prime allocation, which is defined as the difference between the conditional and unconditional allocation. Panel A reports the statistical analysis of prime allocation for hot and cold IPOs, as well as aggregate data for all IPOs. Panel B reports the prime allocation of 5 subperiods, among which 2001-2003 and 2008-2009 are bearish periods, and the rest time periods are bullish periods. The last column tests the significance of the differences in the means, with p-values in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IPOs allocation

	All IPOs	Hot IPOs	Cold IPOs	Test Equality
IPO sample size	2,638	2,073	625	
Initial IPO return				
mean	26.72%	35.88%	-5.24%	(<0.0001)***
median	11.11%	16.92%	-0.67%	
Conditional allocation				
mean	31.12%	33.09%	55.06%	(<0.0001)***
median	6.35%	7.34%	79.61%	
Unconditional allocation				
mean	7.91%	8.35%	37.45%	(<0.0001)***
median	2.45%	2.83%	23.15%	
Prime allocation (ΔP)				
mean	23.21%	24.73%	17.60%	(0.0011)***
median	2.87%	3.39%	2.65%	

Panel B: prime allocation by periods

	Prime allocation (ΔP)			
	All IPOs	Hot IPOs	Cold IPOs	Test Equality
1994-2000				
N	1154	1093	61	
mean	23.93%	25.52%	-4.71%	(<0.0001)***
2001-2003				
N	335	293	42	
mean	25.27%	28.48%	2.82%	(0.0001)***
2004-2007				
N	765	623	142	
mean	22.71%	20.81%	31.08%	(0.001)***
2008-2009				
N	75	57	18	
mean	37.56%	42.60%	21.60%	(0.049)**
2010-2012				
N	302	216	86	
mean	22.27%	23.50%	19.16%	(0.33)

Table 1.4: Regression analysis of IPOs allocation to relationship hedge funds

The table reports estimates of a multivariate regression for 2,638 IPOs offered between 1994 and 2012. The dependent variable is the *Prime Allocation* (ΔP), defined as the difference between the probability that hedge funds get an allocation of IPO conditional on their prime broker-lead underwriter relationships and the unconditional allocation probability. Independent variables include the day one return of the IPO, measured from the offer price to the first-day closing price (*Initial IPO Return*), the percentage difference between the midpoint of the filing range and the offer price (*Pre-IPO Demand*), the natural logarithm of the firm's total assets before the offering (*Log(Issuer Assets)*), the natural logarithm of the IPO offer proceeds (*Log(Proceeds)*), the natural logarithm of the average equity holdings of the hedge fund companies participated in the IPO (*Log(HF Size)*), the average historical relationship participation for the lead underwriter's IPOs over the past five years (*Past Relation*), the lead underwriter reputation ranking obtained from Jay Ritter's web site (*Reputation*), the number of lead underwriters of the IPO (*Lead UW Size*), a high-tech and Internet IPO dummy variable (*HighTech*), and a venture capital backed IPO dummy variable (*VC Backed*). The table reports the estimated coefficients from 1994-2012, among which 2001-2003 and 2008-2009 are bearish periods, and the rest time periods are bullish periods. Standard errors are presented in parentheses. The last three rows report the number of observations, the adjusted R^2, and the F-tests results of each regression. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Prime Allocation (ΔP)					
	All samples		Bullish periods		Bearish periods	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial IPO return	5.842^{***}		5.301^{***}		6.147^{**}	
	(1.238)		(1.389)		(2.888)	
Pre-IPO demand		17.751^{***}		17.602^{***}		N/A
		(6.633)		(6.785)		
Issuer assets (log)	1.420	2.585^{*}	2.008^{**}	2.206	-1.650	
	(0.890)	(1.356)	(0.955)	(1.456)	(2.546)	
Proceeds (log)	4.602^{***}	3.913	3.015^{*}	4.630	6.776^{*}	
	(1.488)	(2.641)	(1.621)	(2.876)	(3.957)	
HF size (log)	-3.418^{***}	-6.166^{***}	-2.834^{***}	-6.673^{***}	-4.307^{***}	
	(0.649)	(1.618)	(0.743)	(1.746)	(1.535)	
Past relation	0.573^{***}	0.482^{***}	0.604^{***}	0.465^{***}	0.447^{**}	
	(0.071)	(0.109)	(0.073)	(0.110)	(0.227)	
Reputation	0.407^{***}	-0.145	0.417^{***}	-0.128	0.290	
	(0.114)	(0.398)	(0.120)	(0.401)	(0.343)	
Lead UW size	1.020^{***}	2.802^{**}	1.217^{***}	2.893^{**}	0.443	
	(0.337)	(1.409)	(0.367)	(1.464)	(0.855)	
HighTech	1.992	3.033	1.292	2.753	4.920	
	(1.819)	(3.188)	(1.933)	(3.239)	(5.096)	
VC backed	-3.092	-2.798	-1.526	-2.103	-13.556^{**}	
	(1.930)	(3.178)	(2.053)	(3.303)	(5.469)	
Constant	28.056^{**}	74.622^{**}	19.590	81.807^{**}	62.779	
	(13.384)	(31.150)	(14.701)	(32.782)	(39.403)	
Time fixed effects						
F-statistics	18.65^{***}	8.90^{***}	17.79^{***}	8.54^{***}	2.85^{***}	
p-value	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(0.0034)	
Industry fixed effects						
F-statistics	19.07^{***}	9.26^{***}	16.06^{***}	8.86^{***}	3.46^{***}	
p-value	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(0.0005)	
Observations	1,263	377	1,036	367	227	10
Adjusted R^2	0.133	0.196	0.138	0.193	0.112	
F Statistic	22.580^{***}	11.164^{***}	19.351^{***}	10.725^{***}	4.158^{***}	

Table 1.5: Regression Analysis of Hedge Fund IPO Investments

The table presents regression analysis of relationship and non-relationship hedge fund investments in IPOs. The dependent variable is the $IA\ Rel._t$ (or, $IA\ Non-Rel._t$), which is calculated as the ratio of relationship (or, non-relationship) hedge fund investments in IPOs to the hedge fund company's asset under management. Independent variables include a dummy variable which is one if the fund company has more than one prime brokers and zero otherwise ($MultiPBs_t$), the number of top ten prime brokers of the fund company ($BigPBs_t$), the number of hot IPOs participated in by the fund company ($HotIPOs_t$), the hedge fund company's return at time $t-1$ ($CReturn_{t-1}$), the quarterly net money flow of fund company at time $t-1$ ($CFlow_{t-1}$), the average age of the managed hedge funds in the fund company at time $t-1$ (Age_{t-1}), and the standard deviation of the return of the fund company at time $t-1$ ($CReturnStd_{t-1}$). The table reports the estimated coefficients using pooled regression with two-way clustered standard errors. Standard errors are presented in parentheses. The last three rows report the number of observations, the adjusted R^2, and the F-tests results of each regression. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable:								
	$IA\ Rel._t$	$IA\ Non-Rel._t$	$IA\ Diff_t$	$IA\ Rel._t$	$IA\ Non-Rel._t$	$IA\ Diff_t$	$IA\ Rel._t$	$IA\ Non-Rel._t$	$IA\ Diff_t$
	(1)	(2)	(3)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)
$MultiPBs_t$	0.226**	−0.702**	0.927***						
	(0.082)	(0.148)	(0.173)						
$BigPBs_t$				0.325***	−0.862***	1.187***			
				(0.103)	(0.192)	(0.223)			
$HOTIPOs_t$							0.580***	0.439***	0.586***
							(0.043)	(0.038)	(0.041)
$CReturn_{t-1}$	−0.507**	0.925**	−1.432***	−0.389*	0.507	−0.897	−0.570***	0.521	−1.091**
	(0.347)	(0.627)	(0.731)	(0.331)	(0.616)	(0.714)	(0.328)	(0.600)	(0.713)
$CFlow_{t-1}$	−0.050	−0.075	0.025	−0.034	−0.122	0.089	−0.018	−0.114	0.096
	(0.091)	(0.164)	(0.191)	(0.087)	(0.162)	(0.188)	(0.087)	(0.158)	(0.188)
$CAge_{t-1}$	0.006	−0.292**	0.297**	0.021	−0.296**	0.317**	0.042	−0.284**	0.326**
	(0.049)	(0.088)	(0.103)	(0.046)	(0.086)	(0.099)	(0.046)	(0.084)	(0.100)
$CstdReturn_{t-1}$	0.222	0.471*	−0.250	0.166	0.427	−0.261	0.213	0.452**	−0.238
	(0.360)	(0.652)	(0.760)	(0.343)	(0.638)	(0.739)	(0.341)	(0.623)	(0.741)
$Constant$	0.308	2.918***	−2.611***	0.099	3.256***	−3.157***	0.082	2.102***	−2.020***
	(0.206)	(0.372)	(0.433)	(0.205)	(0.381)	(0.441)	(0.200)	(0.365)	(0.435)
Observations	911	911	911	970	970	970	970	970	970
Adjusted R^2	0.006	0.040	0.045	0.008	0.031	0.039	0.019	0.076	0.034
F Statistic	2.146*	8.504***	9.581***	2.615**	7.226***	8.854***	4.818***	16.933***	7.826***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.6: Regression Analysis of Hedge Fund Investments in hot and cold IPOs

The table presents regression analysis of hedge fund investments in hot and cold IPOs at the fund company level. The dependent variable is the $IA\ Hot_t$ (or, $IA\ Cold_t$), which is calculated as the ratio of hot (or, cold) IPO investments to the hedge fund company's asset under management. Independent variables include a dummy variable which is one if more than half of the IPOs owned by relationship hedge fund in the fund company, and zero otherwise ($Relationship_t$), the fraction of hedge funds with positive alpha in the fund company $Alpha_t$, a dummy variable which is one if the fund company has more than one prime brokers and zero otherwise ($MultiPBs_t$), the percentage of top ten prime brokers of the fund company ($BigPBs_{i,t}$), the hedge fund company's return at time $t-1$ ($CReturn_{t-1}$), the quarterly net money flow of fund company at time $t-1$ ($CFlow_{t-1}$), the average age of the managed hedge funds in the fund company at time $t-1$ (Age_{t-1}), the standard deviation of the return of the fund company at time $t-1$ ($CReturnStd_{t-1}$), and a dummy variable which is one if more than half of hedge funds use leverage in the fund company, and zero otherwise ($Leverage$). The table reports the estimated coefficients using pooled regression with two-way clustered standard errors. Standard errors are presented in parentheses. The last three rows report the number of observations, the adjusted R^2, and the F-tests results of each regression. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable:		
	IA Hot	*IA Cold*	*IA Diff*
	(1)	(2)	(3)
$Relationship_t$	0.774***	−0.072	0.847***
	(0.198)	(0.103)	(0.238)
$Alpha_t$	−0.225	0.047	−0.272
	(0.180)	(0.069)	(0.198)
$MultiPBs_t$	−0.443**	0.024	−0.468**
	(0.332)	(0.105)	(0.180)
$BigPBs_t$	−0.585**	0.085	−0.670***
	(0.208)	(0.118)	(0.318)
$CReturn_{t-1}$	0.016	−0.017	0.033
	(0.632)	(0.217)	(0.683)
$CFlow_{t-1}$	−0.104	0.037	−0.141
	(0.135)	(0.107)	(0.191)
$CAge_{t-1}$	−0.237**	0.016	−0.253**
	(0.135)	(0.063)	(0.149)
$CReturnStd_{t-1}$	0.465	0.307	0.158
	(0.657)	(0.344)	(0.760)
$Leverage$	0.387*	0.014	0.373*
	(0.221)	(0.098)	(0.206)
$Constant$	3.291***	0.126	3.165***
	(0.221)	(0.207)	(0.457)
Observations	911	911	911
Adjusted R^2	0.054	-0.004	0.045
F Statistic	7.440***	0.553	6.402***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 1.7: Regression Analysis of Post-IPO Hedge Fund Flows

The table presents regression analysis of Post-IPO hedge fund flows and returns on the fund company level. The dependent variable is the quarterly net money flow of the fund company ($CFlow_t$). Independent variables include the average initial returns of the IPOs owned by the fund company at time $t-1$ ($Initial\ IPO\ Return_{t-1}$), the relationship variable, which is calculated as the fraction of IPOs owned by the relationship hedge funds in the fund company at time $t-1$ ($Relationship_{t-1}$), a dummy variable which is one if the fund company has more than one prime brokers and zero otherwise ($MultiPBs_t$), the percentage of top ten prime brokers of the fund company ($BigPBs_t$), the quarterly net money flow of fund company at time $t-1$ ($CFlow_{t-1}$), the hedge fund company's return at time $t-1$ ($CReturn_{t-1}$), the asset under management at time $t-1$ ($CAUM_{t-1}$), the average age of the managed hedge funds in the fund company at time $t-1$ (Age_{t-1}), and the standard deviation of the return of the fund company at time $t-1$ ($CReturnStd_{t-1}$). Column (1) and (2) report the estimated coefficients using OLS regression and logit regression, respectively, with two-way clustered standard errors. Standard errors are presented in parentheses. The last three rows report the number of observations, the adjusted R^2, and the F-tests results of each regression. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable:
	$CFlow_t$
$Initial\ IPO\ Return_{t-1}$	0.047^{**}
	(0.025)
$Relationship_{t-1}$	0.020
	(0.023)
$MultiPBs_t$	0.039^{**}
	(0.017)
$BigPBs_t$	0.0003
	(0.004)
$CFlow_{t-1}$	0.236^{***}
	(0.037)
$CReturn_{t-1}$	-0.064
	(0.072)
$CAUM_{t-1}$ *(log)*	-0.009
	(0.007)
Age_{t-1}	-0.062^{***}
	(0.011)
$CReturnStd_{t-1}$	-0.061^{**}
	(0.073)
Constant	0.421^{***}
	(0.116)
Observations	811
Adjusted R^2	0.136
F Statistic	15.219^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01

CHAPTER 2

TRADING ON PRIVATE INFORMATION: EVIDENCE FROM THE PRIME BROKERAGE AFFILIATED HEDGE FUNDS

2.1 Introduction

An important channel through which hedge funds earn abnormal returns is by trading ahead of sell-side analyst recommendations. Studies have attributed this trading pattern before the public release of recommendations to the leakage of information on analysts' reports. For example, the institutional trades that anticipate changes to analyst recommendations are shown to be consistent with institutional traders receiving tips on analysts' reports (see Irvine, Lipson, and Puckett (2007)). Klein, Saunders, and Wong (2014) and Swem (2014) show that hedge funds trade profitably on analysts' private information by buying before upcoming upgrades and selling before upcoming downgrades, but no similar trading pattern is found for other types institutional traders. In addition, Soltes (2014) and Solomon and Soltes (2015) argue that hedge funds can gain information from the firm management in conjunction with sell-side analysts in private meetings set up by investment bank.

Although information leakage may be the most plausible explanation for the trading activities of hedge funds before the public release of analysts' reports, little evidence has been provided on the underlying motivation and the channel through which information is leaked to hedge funds. According to Klein, Saunders, and Wong (2014), information leakage related to analysts' recommendations occurs between hedge funds and one or two investment banks only. However, the economic incentives that motivate this relationship are not examined. Why do investment banks reveal information or provide information-acquisition opportunity to hedge funds? Why do investment banks favor hedge funds over other investors by providing them profitable investment opportunities?

This study examines whether investment banks are incentivized to provide hedge funds with private information related to their sell-side analysts' recommendations and thereby provides evidence of information leakage. The growth of hedge funds and their demands for investment banking services have produced massive flows of fees for investment banks over the past few years. The business of prime brokerage is highly profitable to investment banks. A 2011 report by Coalition Development Ltd claims that ten largest investment banks earned about $10 billion from prime brokerage business in 2010, which is nearly comparable to the amount earned from their stock tradings[1]. Investment banks, acting as prime brokers, provide a variety of services such as securities lending, margin financing, and settlement facilities to hedge funds. In return, hedge funds boost revenues for investment banks by paying prime brokerage fees on financing spread and trading commissions. Therefore, investment banks need to obtain and retain hedge fund clients. Investment banks compete aggressively for hedge fund clients by providing them with informational advantages or other profitable investment opportunities (see Goldie (2011), Qian and Zhong (2014), Chuang and Kang (2014), and Getmansky, Kazemi, and Yang (2014)).

Investment banks are motivated to share private information related to analysts' reports with hedge funds who use prime brokerage services from the investment banks. If information on analysts' reports leaks, advanced tradings are more likely to be observed with larger magnitude for hedge funds that have prime brokerage affiliations with analysts' employers than for other hedge funds. Other hedge funds may nonetheless trade abnormally before the report release, as experienced hedge funds may learn the related information by analyzing market tradings, reading news, or using alternative information channels. Moreover, hedge funds with short-term investment horizons are more likely to profit from the prime brokerage relationships with analysts' employers by taking advantage of private information and trading on it.

[1] See "Morgan Stanley at Brink of Collapse Got $107 Billion From Fed, Bloomberg Business, Aug 2011".

Herein, I test the hypotheses of selective pre-release of analyst recommendations to the affiliated hedge funds. I define affiliated hedge funds as hedge funds that use reporting analysts' investment banks as their prime brokers. A recommendation is referred to as affiliated if at least one affiliated hedge fund has positions in the covered stock. I hypothesize that hedge funds that have prime brokerage affiliations with an analyst's investment banks display superiority in anticipating that analyst's recommendation. In particular, I test whether tradings of affiliated hedge funds are more likely to vary with the forthcoming analysts' recommendation changes than those of non-affiliated hedge? If hedge funds benefit from investment banks' information leakage, would the affiliated tradings lead to higher profits than non-affiliated tradings?

Combining a comprehensive dataset of hedge funds and analyst recommendations with SEC 13F fillings, I identify the affiliation of hedge funds with sell-side analysts through their investment banks and quarterly equity holdings. Because the intra-quarter timing of hedge fund trades are not available in 13F fillings, I am unable to identify hedge fund trading patterns around the release of analysts' recommendations. Following Klein, Saunders, and Wong (2014), I address this limitation by lining up the recommendations issued up to two trading days following calendar quarter-end dates. For example, suppose March 31 is the quarter-end date reported by hedge funds in Form 13F, and then all recommendations on the first or the second trading day after March 31 will be lined up with the first quarter hedge fund holdings. I believe that hedge fund tradings one or two days before the public release of analysts' recommendations most likely reflect informed trading activities of hedge funds[2]. The regression results bear out my anticipation of the timing of hedge fund trading activities.

[2]Irvine, Lipson, and Puckett (2007) document abnormally high institutional trading volume in the period beginning about five days before the public release of analysts' recommendations. Klein, Saunders, and Wong (2014) find that hedge fund stock tradings up to two days before the analysts' reports are positively correlated with analysts' recommendation changes.

My results support my hypotheses that prime brokerage affiliations motivate the leakage of information on analysts' recommendations and benefit hedge funds. First, I document a positive association between changes in quarterly stock holdings of affiliated hedge funds and changes in the subsequent analysts' recommendations. I find that affiliated hedge funds increase (or decrease) their stock holdings one or two days before the public release of upgrade (or downgrade) recommendations[3]. I do not see the similar association for non-affiliated hedge funds, and neither do I find significant change in hedge fund holdings more than two days before the release of recommendations. These results are consistent with Klein, Saunders, and Wong (2014) that hedge funds trade one to two days prior to recommendation changes.

Second, I find that affiliated large hedge funds tend to buy upgrades and sell downgrades in a larger magnitude compare to non-affiliated hedge funds before the public release of recommendations. The results hold even if analysts do not correctly predict market reactions for downgrade recommendations. In contrast, small hedge funds do not show similar trading pattern difference between affiliated and non-affiliated groups, as small funds tend to generate less prime brokerage fees, on average. Thus, investment banks are less incentivized to share private information with small hedge funds. These results provide strong evidence that affiliated hedge funds especially large ones trade advantageously over non-affiliated hedge funds on forthcoming recommendations, suggesting that investment banks leak information their prime brokerage hedge fund clients.

Third, I show that affiliated hedge funds, either large or small, are more likely to buy upcoming upgrades and sell upcoming downgrades than non-affiliated hedge funds. For each stock, I calculate net trading ratio, the probability that hedge funds trade in a way consistent with upcoming recommendation changes. The net trading ratio is higher for affiliated hedge funds than for non-affiliated hedge funds. The results suggest that, as investment banks

[3]An upgrade (downgrade) refers to a stock recommendation in which the analyst increases (decreases) his buy/sell/hold recommendation rating for the stock.

compete for prime brokerage business, information leakage is more pervasive among affiliated hedge funds, even if they are small hedge funds.

Fourth, I present evidence that the prime brokerage affiliations with investment banks affect hedge fund abnormal returns. Hedge funds cannot benefit from banks' information leakage if analysts' recommendations have little impact on the stock price movements. I show that affiliated hedge funds earn higher short-term abnormal returns by buying before upgrades than do non-affiliated hedge funds; meanwhile, the prime brokerage affiliations with analysts' investment banks help hedge funds avoid negative or relatively low short-term abnormal returns induced by downgrade recommendations. These results suggest that affiliated hedge funds are more likely to obtain profitable information on upcoming recommendations from investment banks.

These results are robust to alternative explanations. In particular, I analyze the investment values of hedge funds by controlling for star analysts and influential recommendations. I find that prime brokerage affiliations with analysts' investment banks have positive impacts on hedge funds' abnormal returns no matter whether the analysts are star analysts or not. Similar patterns of abnormal returns are observed for hedge funds that trade ahead of non-influential recommendations. However, for influential recommendations, abnormal returns are comparable across affiliated and non-affiliated hedge funds, suggesting that investment banks tend to cater to their hedge fund clients in an inconspicuous way.

I also provide evidence that the relatively high abnormal returns earned by affiliated hedge funds cannot be attributed to fund managers' skills. Rather, it owes to investment banks that add values to hedge funds by providing them with profitable investment opportunities. Moreover, investment banks are more likely to show favoritism to the affiliated hedge funds with higher skills, in expectation that they can earn more future rewards from the hedge funds.

This study relates to three strands of literature. First, this study contributes to the literature by demonstrating the incentive and consequence of information leakage of analysts' reports. More important, I examine the incentives of investment banks to provide hedge funds with information on analysts' reports. Analysts may have strong incentives to leak information because the relationships with institutional investors help their brokerage firms generate additional commission revenue and thus make them receive higher compensation (see Irvine (2004), Jackson (2005), Groysberg, Healy, and Maber (2011), Maber, Groysberg, and Healy (2014)) or get job offers from prestigious investment banks (see Hong and Kubik (2003), Hong, Kubik, and Solomon (2000)). Moreover, analysts rely on institutional investors to build career reputations, as institutional investors periodically evaluate analysts' performance by electing All-America Research Team (see Leone and Wu (2007), Ljungqvist, Marston, Starks, Wei, and Yan (2005)) or choosing which brokerage firms to use (see Maber, Groysberg, and Healy (2014)). This paper complements the prior research by studying the tipping behavior induced by prime brokerage business relationships between hedge funds and investment banks, as prime brokerage fees are an important source of revenue earned by investment banks.

Second, this paper contributes to the growing literature of leaking information on analysts' reports to institutional investors. Irvine, Lipson, and Puckett (2007) document an increase in institutional tradings before the announcement of initial buy or strong buy recommendations. Correspondingly, Christophe, Ferri, and Hsieh (2010) show an abnormally high level of short selling before downgrade recommendations. In both papers, either buying or selling before recommendations presents evidence for potential information flows from analysts to institutional investors. This paper is most closely related to Klein, Saunders, and Wong (2014) and Swem (2014), which find a positive correlation between hedge fund trading and the subsequent changes in analysts' recommendations and no obviously similar trading patterns for other institutional investors. However, these authors do not test the underlying motives of information leakage, neither do they differentiate between investors that have interest-driven relationships with analysts' brokerage firms from those without such relationships. This paper complements and extends previous studies by comparing trading behaviors of investors in different relationship groups.

Third, this paper provides strong support for the beneficial role of prime brokers in hedge funds' equity investments. Getmansky, Kazemi, and Yang (2014) find that investment banks support hedge fund investments and growth by allocating underpriced IPOs, especially for start-up hedge funds or poorly-performed hedge funds. Other related studies focus on the information provision role of prime brokers. Qian and Zhong (2014) study hedge funds' possession of private information through post-IPO stock abnormal returns. They show that connections between prime brokers and IPO underwriters are an important source of private information for hedge funds. Goldie (2011) finds that risk arbitrage hedge funds are more likely to invest in mergers and acquisitions (M&A) when hedge funds' prime brokers also work as advisors in the deals, and hedge funds outperform naive portfolios of risk arbitrage investment by gaining information advantages through their connections with investment banks. Chuang and Kang (2014) examine the comovement of hedge fund returns and argue that the strong comovement in hedge fund returns is induced by valuable information provided by prime brokers. I find that information leakage of analysts' recommendations provide another channel that investment banks reward their hedge fund clients and boost their competitiveness in the prime brokerage businesses.

The remainder of this paper is organized as follows. Section 2.2 discusses the hypotheses and my research design. Section 2.3 describes sample construction and presents summary statistics. Section 2.4 presents methodologies and test results of comparing the trading activities of affiliated and non-affiliated hedge funds. Section 2.5 shows the difference of abnormal returns between affiliated and non-affiliated portfolios. Section 2.6 concludes.

2.2 Hypotheses and research design

As investment banks are motivated to attract and retain hedge funds as clients, they tend to reveal information or provide information-acquisition opportunity to their hedge fund clients. Thus, prime brokerage affiliation creates a potential channel for information flows between investment banks and hedge funds. Based on my discussion thus far, I state the hypotheses as follows.

Hypothesis 1: Hedge funds are more likely to acquire private information on upcoming stock recommendations if they use prime brokerage services from the reporting analysts' investment banks.

If analysts' investment banks provide prime brokerage services to hedge funds, the trading demands of hedge funds are predicted to be more likely to vary with upcoming recommendations. Meanwhile, more hedge funds will buy stocks on upcoming upgrades and sell stocks on upcoming downgrades if they use prime services from the analysts' employers.

Hypothesis 2: Hedge funds are more likely to acquire profitable information on upcoming stock recommendations if they use prime brokerage services from the reporting analysts' investment banks.

If analysts' investment banks provide prime brokerage services to hedge funds, the quality of acquired information on forthcoming recommendations is expected to be higher. Thus, hedge funds are more likely to receive accurate information on analysts' reports, and their investment values tend to be correlated with upcoming recommendation changes. Moreover, as analysts cater to hedge funds by providing them with profitable investment opportunities, the short-term investment values of affiliated tradings are expected to outperform those of non-affiliated tradings.

To test these hypotheses, I model hedge funds' information acquisition as trading in a way consistent with upcoming recommendation changes shortly before the public release of recommendations. I use Form 13F to identify hedge fund quarterly holdings, as well as changes in stock holdings. Thus, I am able to determine hedge funds' buying or selling activities through the increase or decrease of their stock holdings over a particular quarter. I associate hedge fund trading with analyst recommendations on the same stocks issued one or two days subsequent to 13F filing date. I believe that buying or selling stocks immediately prior to recommendation release date will most likely capture the activities induced by information flows from investment banks to hedge funds.

In order to separate the effect of each recommendation, I remove samples that associate quarter-end hedge fund holdings with recommendations in both the following 1st and 2nd day. I include yearly fixed effects to control for macroeconomic effects and cluster the standard errors by hedge funds, investment banks, and stocks, respectively. The settings of tests are not subject to earnings announcement drift.

2.3 Sample construction and summary statistics

I construct the sample by compiling a comprehensive dataset of hedge fund equity holdings and analyst recommendations. The final samples include a universe of 176 hedge fund management companies with 11 prime brokers and 750 recommendation changes with 550 sell-side analysts, spanning the period from 2003 to 2012.

2.3.1 Hedge fund sample

I use TASS database to identify all the hedge funds and hedge fund management companies. The TASS database is one of the most comprehensive hedge fund database consisting of monthly hedge fund returns, asset under management (thereafter, AUM), and other fund-specific information. More importantly, it provides information on prime brokers which is useful in identifying the special association of hedge funds with investment banks.

I identify hedge fund equity holdings based on institutional holdings from 13F fillings to Securities and Exchange Commission (SEC). As a private investment company, hedge funds with more than $100 million under management must report their holdings to the SEC each quarter on form 13F, including all long positions (but no short position) in U.S. stocks and a few other securities greater than 10,000 shares or $200,000 in the market value. Holdings are reported at the management company level at the end of each calendar quarter.

Following the methodology of Brunnermeier and Nagel (2004) and Griffin and Xu (2009), I compile a list hedge fund management companies from TASS hedge fund databases, and manually match them with the companies registered as investment advisers from 13F database. If a firm is not registered, I include it in the sample, since registration is a pre-requisite for conducting non-hedge fund business such as advising mutual funds and pension plans. If the firm is registered, I obtain its ADV form and check its eligibility for the sample based on two criteria: (1) at least 50% of its clients are Other pooled investment vehicles (e.g., hedge funds)" or High net worth individuals," and (2) it charges a performance fee for its advisory services. This process leaves us with 380 companies and 25,633 total stock holdings.

To identify hedge funds holdings in long positions, I focus solely on hedge funds using long/short equity hedge, equity market neutral, Multi-Strategy, and event driven strategies. I used data for both Live" and Graveyard" funds to mitigate a potential survivorship bias. Since holdings data are company-based, I upgrade fund-level characteristics to the company-level to satisfy the consistency requirements. For example, a hedge fund company's asset under management is calculated as the sum of AUMs of all hedge funds managed by the company at each time point. I include only hedge funds that have at least $1 billion of assets under management and have no less than 6 quarters of observations.

An important motive for using TASS is that it provides information on prime brokers that a hedge fund requests services from. In recent years, the demand of hedge funds has boosted the revenues of investment banks through their prime brokerage divisions. The core services offered by a prime broker include execution and custody, margin financing, securities lending, and consolidated reporting. As hedge funds continue to grow, prime brokers are quickly expanding their businesses to include services such as risk management and capital introduction.

In TASS, prime brokers are cross-sectionally identified at fund level, and a hedge fund may be associated with one or more prime brokers. Since a management company often offers multiple hedge funds, I use all listed prime brokers within the same institution for a hedge fund company. The unreported summary statistics of filtered TASS database consists of 1,220 hedge fund companies and 343 prime brokers. The prime brokers are reported by 49% of hedge funds, among which about 17% declare to have multiple prime brokers. In the sample, I excluded funds that did not report information on their prime brokers.

For most hedge funds, a prime brokerage, especially the division of a large investment bank, is indispensable to the operation and ultimate success of their businesses. According to the snapshots of TASS data from 2006 to 2012, the eleven major prime brokers ranked by their average market share were Goldman Sachs, JP Morgan, Morgan Stanley, Credit Suisse, Deutsche Bank, UBS, Citi, Lehman Brothers, Bear Stearns, Bank of America, and Merrill Lynch. TASS lists 465 global prime brokers, with the 11 biggest prime brokers accounting for about 86% of the market share in hedge fund businesses. Therefore, I include only these 11 largest prime brokers in this study.

I examine the prime broker turnover using yearly snapshots from 2006 to 2012. I do not find significant changes of prime brokers for each hedge fund company and neither do the changes of multiple prime brokers over these years. As the relationships between hedge funds and prime brokers are relatively stable in this sample, I use prime broker data in 2006 snapshot for the time-series sample construction prior to 2006.

In additional to the hedge fund holdings, I also identify the holdings of other institutional investors using the form 13F. The 13F institutions are classified into six types of institutional investors: (1) Banks, (2) Insurance companies, (3) Investment companies (or mutual funds), (4) Independent investment advisors, (5) Hedge funds, and (3) All others. I identify the other institutional investors by combining all non-hedge fund categories into one group.

2.3.2 Analyst recommendation sample

I obtain stock recommendations data from Thomson Financial's Institutional Brokers Estimate (I/B/E/S) detail file, which identifies the names of analysts covering a given stock, the broker codes, the stock ratings, and the report date. I build the sample by searching for stock ratings issued by individual analysts in particular brokerage firms from 2003 to 2012[4], with ratings ranging from 1 (strong buy) to 5 (strong sell). I reverse the ratings (e.g. strong buy now is denoted by 5 and strong sell now is denoted by 1) to allow higher ratings to correspond to more favorable recommendations.

I focus on recommendation revisions rather than mere levels, since recommendation changes are more informative on future stock values (see Jegadeesh and Kim (2009), Loh and Stulz (2011)). The recommendation change (Δrec) is computed as the current rating minus the prior rating by the same analyst, with the value ranging from -4 to +4. A recommendation upgrade is defined as a positive recommendation change, and a recommendation downgrade refers to negative recommendation change. I remove analysts coded as anonymous by I/B/E/S and lack of brokerage house information. I also remove observations for which fewer than three analysts have active ratings. Each stock in the sample should have at least one analyst who issues one recommendation and then another within 6 months.

I obtain analysts' brokerage house information by mapping broker codes in the detail file to names of brokers in the translation file[5] . The translation file is no longer available in I/B/E/S subsequent to 2005, but most of the broker codes are still being used by I/B/E/S. Therefore, I use the latest version of the file associated with searching through LexisNexis, Bloomberg, and Google to identify the brokerage house that the analysts work for after 2005.

I identify the affiliation of hedge funds with sell-side analysts by manually matching analysts' brokerage firms with the prime broker(s) that a hedge fund is associated with from the TASS hedge fund database. The affiliated trading is then identified as a hedge fund's buying/selling a stock if the hedge fund is affiliated with a sell-side analyst's investment

[4]Prior to the issuance of National Association of Securities Dealers (NASD) rule 2110 in 2002, analysts are compensated through their services to investment bank. As a result, member firms of analysts' invest bank may trade based on the pre-released analysts' research reports. Therefore, rating samples before 2003 are likely to bias the test results for the affiliated trading.

[5]I am grateful to Alexander Ljungqvist for sharing the translation file with me.

bank. The stock information including return, share price, and turnover are from Center for Research in Security Prices (CRSP).

2.3.3 Summary statistics

Table 2.1 reports summary statistics of the samples from 2003 to 2012 with hedge fund holdings lined up to two days before the release of recommendations. Panel A shows a total of 3,698 cumulative stock recommendations in the sample, with 1,309 upgrades, 1,796 downgrades, and 593 no changes. Among these recommendations, approximately 47% are one level changes, 36% are two level changes, and only less than 1% are three or four level changes. Panel B shows the cumulative number of recommendation changes by years over the sample period. On average, 370 recommendations change each year, with the number of downgrades greater than that of upgrades and no changes. More firms receive upgrade and downgrade recommendations in bull market than in bear market.

As Panel C shows, I capture the trading of 176 hedge funds in 750 recommendation changes which are reported by 550 analysts from 11 investment banks. In order to examine the impact of prime brokerage affiliations, I divide hedge fund trading into two groups: affiliated and non-affiliated. Among the 3,698 hedge fund tradings, about 30% are affiliated and 70% are non-affiliated. I further show the size effect of hedge funds on its tradings. I refer to hedge funds with asset under management no less than $1 billion as large hedge funds, and small hedge funds otherwise. For large hedge funds, which account for about 33% total hedge funds in the sample, 31% of tradings are affiliated and 69% are non-affiliated. The affiliated tradings of small hedge funds account for 42% of their total tradings, which is relatively higher than that of large funds.

Panel C also show descriptive statistics for subsamples that will be used for robustness tests in this study. I define Net-rec as hedge funds that trade in the same direction as recommendation changes and Net-rec I as subsamples of Net-rec in which hedge fund tradings have different signs than those of stock abnormal returns in the corresponding month. I show that, for affiliated hedge funds, approximately 37% of trading is in the same direction as recommendation changes, among which 43% have different signs than those of the monthly stock abnormal returns. For non-affiliated hedge funds, Net-rec and Net-rec I account for 40% and 18% total hedge fund tradings, respectively.

Panel D reports the characteristics of analysts, stocks, and hedge funds for the full sample from the TASS hedge fund database matched with 13F institutional holding data and I/B/E/S database from 2003 through 2012. The characteristics include analyst experience, which is calculated as the number of years since an analyst issued the first recommendation on I/B/E/S, coverage, which is the number of analysts that issued at least one recommendation for a firm over a quarter, market value (in millions), quarterly stock return, quarterly stock turnover, hedge fund AUM (in millions), which is calculated as the sum of AUMs of all hedge funds managed by a company at a quarter, hedge fund quarterly return, which is calculated as the percentage change of the net asset values of the fund company between the beginning and the end of a quarter, and hedge fund age (in months), which is calculated as the asset weighted average age of the managed hedge funds. All these variables are used as control variables in regression analyses in section 4.3.

2.4 Affiliation and information acquisition

I begin the analysis by comparing the trading patterns of affiliated hedge funds with non-affiliated hedge funds. I also examine how hedge fund tradings relative to other institutional investors vary with the changes of information. Then I use regression analyses to test whether prime brokerage affiliations impact information acquisition of hedge funds.

2.4.1 Hedge fund trading measures

I use three measures to evaluate trading activities of hedge funds prior to the release of analysts' recommendations based on the Form 13F. The first measure is the holdings change ($\Delta shares_{j,i,t}$) of a hedge fund j, which is defined as the change in the number of shares held by the hedge fund in stock i during quarter t. The holdings change represents hedge fund's net buys or net sales of a particular stock over a quarter, which directly reflect the trading activities of hedge funds before the release of recommendations.

$$\Delta shares_{j,i,t} = shares_{j,i,t} - shares_{j,i,t-1} \tag{2.1}$$

Presumably both hedge funds' buying and selling activities and analysts' recommendation changes are based on the anticipated stock market value. For example, hedge funds may buy more stocks with lower price and purchase fewer stocks that are more expensive. As a result, holding quantity based measure may bias the tests of information leakage to hedge funds. Therefore, as an alternative to holdings change, I define net trading value ($\$\Delta shares_{j,i,t}$) as the dollar turnover of hedge fund j's holdings in stock i over quarter t.

$$\$\Delta shares_{j,i,t} = (shares_{j,i,t} - shares_{j,i,t-1}) * p_{i,t} \tag{2.2}$$

where $\Delta p_{i,t} = p_{i,t} - p_{i,t-1}$, and $p_{i,t}$ and $p_{i,t-1}$ is the share price of stock i at the end of quarter t and $t-1$, respectively. This measure is designed to control for the impact of level and movement of stock price on hedge fund trading.

The last measure is used to examine the likelihood of informed trading of hedge funds prior to recommendation changes. I introduce the net trading ratio ($NTR_{i,t}$), which is calculated as the number of hedge funds js that trade in the same direction as recommendation change released on day d ($d > t$) on stock i scaled by the total number of hedge funds in the sample in quarter t.

$$NTR_{i,t} = \frac{\sum\limits_{j \in HFSample} HF_{j,i,t} \; with \; sign(\Delta shares_{j,i,t}) = sign(\Delta rec_{i,d})}{\sum\limits_{i \in RecSample} \sum\limits_{j \in HFSample} HF_{j,i,t}} \tag{2.3}$$

Different than the previous two measures, the net trading ratio is calculated on the stock level. If the direction of a hedge fund's trading is consistent with a recommendation change, the hedge fund might have acquired information on the analyst's report. If not, the hedge fund either did not receive information or traded with its own skill. To the extent that trading ahead explains information leakage, the net trading ratio measures the probability of information-induced trading of hedge funds, and the higher ratio indicates the higher probability of information leakage.

To examine information-induced trading, I categorize all hedge fund samples into two groups: affiliated and non-affiliated, and further divide each group into large and small hedge funds. Investment banks are more likely to cater to hedge funds that are their business clients, considering massive prime brokerage fees earned from these high net-worth investors. In addition, investment banks prefer to serve large-size hedge funds, as they possess a large amount of capitals and are expected to pay higher fees on financing spread and trading commissions. Therefore, considering the impact of fund size on banks' payback, I partition hedge funds into large and small funds based on their assets under management, with a threshold of $1 billion. If information leakage occurs, affiliated large hedge funds are expected to display superiority in pre-release trading relative to other funds.

Table 2.2 and Figure 3.1 presents statistical analysis for the trading of affiliated and non-affiliated hedge funds prior to the release of recommendations. I separately test the trading of large and small hedge funds in upgrade and downgrade recommendations using three measures. Table 2.2 Panel A presents results for upgrade recommendations. The means and medians of the three measures are all positive for both large and small funds. For the affiliated large hedge funds, the average increments of share holdings and net trading values prior to the recommendation release are significantly greater than those of non-affiliated large hedge funds and small hedge funds. In contrast, small hedge funds do not show similar trading pattern differences between the affiliated and non-affiliated groups. In terms of the net trading ratio, affiliated hedge funds show significant advantages over non-affiliated funds, either large or small funds, in buying upcoming upgrades beforehand. I do not observe obvious difference of net trading ratios between large and small hedge funds with prime brokerage affiliations.

For downgrade recommendations, as shown in Table 2.2 Panel B, the average share holdings and net trading values still increase over a quarter prior to the recommendation release. However, the magnitudes of increments for affiliated large funds are significantly smaller than those of non-affiliated large hedge funds and small hedge funds. In addition, the average net trading ratio of selling upcoming downgrades is significantly higher for affiliated hedge funds than for non-affiliated funds. The average net trading ratio of selling downgrades is comparable across large and small hedge funds.

These results provide evidence that affiliated hedge funds especially large ones trade advantageously compared to non-affiliated hedge funds on forthcoming recommendations. Specifically, affiliated large hedge funds tend to buy more upgrades and sell more (or buy less) downgrades prior to the release of recommendations than do non-affiliated hedge funds. The results suggest the existence of information leakage on analysts' recommendations due to prime brokerage business relationships. I also find that, consistent with the profit-driven nature of the banking business, the magnitude of information leakage is positively related to fund size, as investment banks earn higher prime brokerage fees from large hedge funds. Small hedge funds may also acquire private information from investment bank, as their prime brokerage affiliations are associated with a higher likelihood of information-induced trading.

2.4.2 Information acquisition and trading demand

I further examine how hedge fund tradings vary with the change of information under the impact of prime brokerage affiliations. According to Kacperczyk and Seru (2007), if investors receive more precise private information before the release of a recommendation, they are more sensitive to information than less-informed investors and trade advantageously on it. As information goes from private to public, demands of less-informed investors are more responsive to public information than those of informed investors. Thus, less-informed investors tend to boost (or cut) their holdings relative to informed investors after upgrade (or downgrade) recommendations are released. Based on this, I ask whether hedge funds show a similar trading pattern, and whether prime brokerage affiliation is an important determinant of this pattern?

Tests are based on the noisy Rational Expectations Equilibrium model of Grossman and Stiglitz (1980), which argues that as the quality of informed traders' information increase, the more their demands will vary with the information. In this paper, the premise of the argument is that prime brokerage affiliations with analysts' investment banks lead to more precised private signals received by hedge funds. Given this premise, if hedge funds receive prime brokerage services from analysts' investment banks, their aggregate demands for the forthcoming recommendations will change more with the change of information than will those of non-affiliated funds.

I estimate relative trading demands of affiliated and non-affiliated hedge funds and test their difference prior to and after the release of recommendations. Relative trading demand is defined as the trading demand of hedge funds relative to that of other institutional investors. For each recommendation change, trading demand is calculated as the percentage changes of aggregate stock holdings in a quarter. I use the demand of other institutional investors as a benchmark in order to control for factors unrelated to information leakage[6].

In the unreported tests, trading demands are asymmetrically distributed, with the value spans from -0.42 to 7.502 for hedge funds and from -0.098 to 0.307 for other institutional investors. For large hedge funds, the average pre-release demand for upgrades is significantly greater than that of other large institutional investors, either affiliated or non-affiliated. I do not observe a particular pattern for small hedge funds and for the post-release trading. These results indicate that, relative to hedge funds, other institutional investors are uninformed of

[6]According to Klein, Saunders, and Wong (2014) and Swem (2014), other institutional investors do not show similar pre-recommendation trading patterns of buying upgrades and selling downgrades as hedge funds, suggesting that other institutional investors are uninformed relative to hedge funds.

the upcoming analyst reports. Hedge funds trade actively in certain stocks and are among the most important players in equity market.

Table 2.3 presents the statistical analyses of relative trading demand of affiliated and non-affiliated hedge funds prior to (pre) and after (post) the release of analyst recommendations. I value-weight investors' demand for each stock by dividing investors' holding values in a stock with their holding values in all stocks in a quarter. I test the mean and median difference of pre-release and post-release relative demand for the two groups of hedge funds using a paired t-test and Wilcoxon rank-sum test. I separately show the results for large and small hedge funds, as well as the mean trading demand of other large and small institutional investors.

Panel A shows that, for upgrade recommendations, the pre-release relative trading demand of large hedge funds, either affiliated or non-affiliated, are significantly higher than their post-release relative demand. Two sample Wilcoxon rank-sum test shows that the average pre-release relative demand of affiliated large hedge funds is significantly greater than that of non-affiliated funds, whereas post-release tradings do not show a similar pattern. For the affiliated large hedge funds, the average variation of relative demand from pre- to post-release is 1.362, which is greater than 0.920 for the non-affiliated large hedge funds at 5% significance level. I do not observe similar demand patterns for the small hedge funds. These results provide evidence that large hedge funds especially affiliated ones tend to buy pre-release upgrades and reverse the trades after the release of recommendations.

Panel B presents the statistical analysis of relative trading demand around downgrade recommendations. The paired t-test results are not quite straightforward, as the potential decreases in demands are balanced out by big trades of large hedge funds. Nonetheless, I find that, for the affiliated large funds, the median relative demand is negative, suggesting that the probability that hedge funds sell more (or buy less) pre-release downgrades than other institutional investors are above fifty percent. Moreover, unlike non-affiliated hedge funds, the average pre-release relative trading demand of affiliated hedge funds is not significantly higher than post-release relative demand, which is consistent with the test results for upgrade recommendations.

In sum, the analyses of relative trading demand in Table 2.3 provides support for the hypothesis, as affiliated hedge funds have a higher (or lower) pre-release trading demand for upgrades (or downgrades) than non-affiliated funds. More important, consistent with Kacperczyk and Seru (2007), the results suggest that affiliated hedge funds are sensitive to private information prior to the recommendation release and are less likely to rely on public information in the post-recommendation tradings than are non-affiliated hedge funds. These results illustrate the importance of prime brokerage affiliations on the information acquisition of hedge funds.

2.4.3 Regression analysis of pre-release hedge fund trading

To test whether hedge funds that have prime brokerage affiliations with analysts' investment banks are more likely to obtain private information on analysts' reports, I start by examining the timing of hedge fund trading prior to recommendation changes. I include additional 22,109 recommendation change samples, which are issued up to 10 trading days following the Form 13F quarter-end date. I line up these recommendation changes with hedge fund quarterly holdings from the Form 13F. The total samples for the timing test consist of 62 large hedge funds and 133 small hedge funds associated with 7,917 affiliated tradings and 17,890 non-affiliated tradings.

Following Klein, Saunders, and Wong (2014), I form 10 portfolios by assigning each recommendation change to a portfolio based on k days between the Form 13F quarter-end date t and the release date of recommendation d. I run the regression $\Delta share_{j,i,t} = \alpha_k + \beta_k \Delta rec_{i,d} + \epsilon_{i,k}$, where $\Delta share_{j,i,t}$ is the change in the number of shares held by hedge fund j in stock i during quarter t, and $\Delta rec_{i,d}$ is the change of an analyst's recommendation for stock i issued on day d ($d = t+k, k = 1, 2, ..., 10\ day(s)$). Yearly fixed effects are included, and standard errors are clustered by hedge funds and investment banks. The estimated β_k infers whether hedge funds trade k day(s) prior to recommendation release.

Table 2.4 reports results for the estimated β_k for each portfolio, with the last row shows results for the aggregated 5 portfolios from day $d = t + 6$ to $t + 10$. I separately estimate β_k for the affiliated and non-affiliated hedge funds. The results show that only β_1 and β_2 for affiliated hedge funds are positive and significant, and β_k from $d = 3$ to $d = 10$ are insignificant for any group of hedge funds. Consistent with Irvine, Lipson, and Puckett (2007) and Klein, Saunders, and Wong (2014), these results provide evidence that affiliated large hedge funds trade one or two days prior to recommendation changes, suggesting the existence of information leakage of analysts' recommendation. Therefore, in order to examine the effect of prime brokerage affiliations on hedge fund trading, I focus on recommendations issued up to two trading days following the Form 13F quarter-end date throughout the rest of this paper.

I then perform three sets of multivariate regressions on hedge fund tradings, which are measured using $\Delta shares$, $\$\Delta shares$, and NTR, respectively, to examine trading activities of individual hedge funds prior to recommendation changes. As discussed above, hedge funds are categorized into four groups: affiliated large, non-affiliated large, affiliated small, and non-affiliated small, and I generate a corresponding dummy variable for each group: AL, NAL, AS, and NAS. I use the non-affiliated small group as a base group and include the other three dummy variables along with their interactions with Δrec in the regression. I include a vector of variables for stocks, analysts, and hedge funds to control for factors influencing hedge fund tradings. Analyst experience (*Ana exp*), which is calculated as the number of years since an analyst issued the first recommendation on I/B/E/S, controls for the effect of analyst experience on hedge fund tradings. Analyst coverage (*Coverage*), which is the number of analysts that issued at least one recommendation for a firm over a quarter, captures the impact of analyst opinions on fund tradings. The logarithm of stock market value (*Ln MV*) from the previous year, stock return (*Stk return*) over previous quarter, and stock turnover (*Stk turnover*) over previous quarter are used to control for the effect of firm size, stock return and turnover on fund tradings, respectively. $HF\ flow$ is the quarterly flow of a hedge fund company, calculated as the percentage change of AUMs of a fund company between the beginning and the end of a quarter. Hedge fund return ($HF\ return$), which is calculated as the percentage change of net asset values of a fund company between the beginning and the end of the previous quarter, controls for fund performance effect. Hedge fund age ($HF\ age$), which is calculated as the asset weighted average age (in months) of the managed hedge funds, controls for the fund age effect.

Table 2.5 reports test results of pre-release hedge fund tradings measured by $\Delta shares$ and $\$\Delta shares$. Panel A shows the regression analysis for all hedge funds, Panel B presents the results of equality tests for the differences between regression coefficients in different groups, and Panel C, D, and E present the regression results for large hedge funds only. I include yearly fixed effect in the regressions, and standard errors are clustered by hedge funds and investment banks.

Panel A shows regression results for total recommendation changes, as well as non-negative and non-positive recommendation changes. In all models, the coefficients on interaction terms of Δrec and AL are positive and significant, indicating that affiliated large hedge funds tend to buy more shares for bigger upcoming upgrades and sell more shares for bigger upcoming downgrades. This result suggests that tradings of affiliated large hedge funds are positively associated with the forthcoming recommendation changes with the magnitude greater than that of the base group. The coefficients on Δrec and $\Delta rec \times NAL$ are not significant and are even significantly negative on $\Delta rec \times AS$ for the total and non-positive recommendation change samples, suggesting that the tradings of small hedge funds and non-affiliated hedge funds are inconsistent with the upcoming recommendation changes.

I also compare the trading behavior of three non-base groups by testing the differences of regression coefficients. Panel B presents F-stats of the equality tests between coefficients on three interaction variables. For the regressions of both $\Delta shares$ and $\$\Delta shares$, the coefficients of $\Delta rec \times AL$ are significantly bigger than those of $\Delta rec \times NAL$ and $\Delta rec \times AS$, suggesting that affiliated large hedge funds are more likely to buy upcoming upgrades and sell upcoming downgrades in a larger magnitude compared to other hedge funds. These results provide evidences on the information leakage hypothesis that affiliated large hedge funds are more likely to acquire private information on upcoming stock recommendations.

I perform the robustness tests by undertaking regression analyses for large hedge funds only. If information leakage is present, affiliated large hedge funds are expected to buy upgrades and sell downgrades prior to the release of reports even if analysts do not correctly predict market reactions. Thus, I define Net-rec as hedge funds that trade in the same direction as upcoming recommendation changes and Net-rec I as subsamples of Net-rec in which hedge fund tradings have different signs than those of stock abnormal returns in the corresponding month. The monthly stock abnormal returns are estimated from the Fama-French-Carhart (see Carhart, 1997) four-factor model[7].

Panel C, D, and E in Table 2.5 present the regression results of upgrades & downgrades respectively, and for the total samples of large hedge funds, Net-rec, and Net-rec I, separately. For the regressions of both $\Delta shares$ and $\$\Delta shares$, the coefficients on $\Delta rec \times AL$ are positive and significant for the total samples and for the Net-rec samples in upgrades & downgrades. These results are consistent with the previous test results. More importantly, the results provide strong evidence that affiliated large hedge funds are privately informed on analysts' recommendations and they trade ahead by taking advantage of it.

As a result of robustness check, the coefficients on $\Delta rec \times AL$ for Net-rec I in the regressions of both $\Delta shares$ and $\$\Delta shares$ are significant and positive in the downgrades samples in Panel E. The results provide evidence that hedge funds are likely to sell prior to the release of downgrade recommendations, even if the expected stock price downward heading does not occur. However, for upgraded stocks with negative post-event abnormal returns, I

[7]I am grateful to Kenneth French for making the data on the four factors available for download from his website at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

do not find the similar trading patterns. A potential explanation is that analysts are more likely to tip off hedge funds on the upcoming downgrade recommendations than on upgrade recommendations. According to Barber et al. (2005), analysts are reluctant to downgrade stocks that are predicted to have dimming prospects. With a downgrade recommendation, the subsequent stock price is more likely to head downward, relative to the chances of heading upward after a upgrade recommendation. Therefore, private information on downgrades is more valuable than that on upgrades for hedge funds with prime brokerage affiliations.

Another possible reason is that investors are downside risk averse. If information uncertainty is high, hedge funds would rely more on its own skills or other information sources than purely on private information from analysts to trade stocks with bright prospects. However, for the expected downgraded stocks, affiliated hedge funds tend to put more weight on analysts' opinions and reduce their shares holding more than they should have done based on the acquired information. As a result, the difference of trading sensitivity to downgrade information between affiliated and non-affiliated hedge funds become larger, compared to funds' reactions to upgrade information. In addition, information leakage of downgrade recommendations may lead to greater short selling of hedge funds with prime brokerage affiliations, which is beyond the discussion of this paper and requires further data supports.

To examine the pervasiveness of information leakage, I further perform stock-level regression analyses of the pre-release hedge fund trading measured by the net trading ratio (NTR).

$$NTR_{i,t} = \alpha_d + \beta_{1d}\Delta rec_{i,d} + \beta_{2d}AR_{i,d} + \beta_{3d}\Delta rec_{i,d} \times AR_{i,d} + \gamma_d X_{i,t-1} + \epsilon_{i,d} \tag{2.4}$$

where $\Delta rec_{i,d}$ is the change of an analyst's recommendation for stock i issued on day d, which is one or two trading days following the Form 13F report date t ($d = t+1$ or $t+2$), $AR_{i,d}$ is a dummy variable indicating whether the recommendation is affiliated, that is, whether at least one affiliated hedge fund has positions in the stock i, $\Delta rec_{i,d} \times AR_{i,d}$ is an interaction variable of $\Delta rec_{i,d}$ and $AR_{i,d}$, and $X_{i,t-1}$ is a vector of control variables for analysts and stocks in quarter $t-1$, including *Ana exp*, *Coverage*, *Ln MV*, *Stk return*, and *Stk turnover*.

I separately compute NTR for large hedge funds and small hedge funds, denoted as NTR_L and NTR_S, respectively, and estimate a system of two equations simultaneously using seemingly unrelated regressions (SUR). I do not use independent ordinary least squares (OLS) estimation for the two equations because the error terms in the two models are correlated, and using a joint estimation than OLS is more efficient.

Table 2.6 reports the results of SUR tests, with Panel A presents the regression analysis for upgrades and downgrades and Panel B presents the results of equality tests for the coefficient differences between large and small hedge funds. As Panel A shows, in both models, the coefficients on Δrec and $\Delta rec \times AR$ are significantly positive for upgrade recommendations and significantly negative for downgrade recommendations. These results provide evidence that larger upgrade (or downgrade) recommendations are associated with higher percentages of stock purchase (or selling) by hedge funds, either affiliated or non-affiliated. More importantly, I find that affiliated hedge funds have a significantly higher probability to trade in a way that is consistent with upcoming recommendation changes than non-affiliated hedge funds. The results suggest the existence of information leakage from investment banks to affiliated hedge funds.

These results hold even for small hedge funds, indicating that not merely large hedge funds but small hedge funds acquire more or less information on analysts' recommendations. There might be other channels through which hedge funds obtain private information on stock trading, however, the positive coefficients on $\Delta rec \times AR$ suggest that small hedge funds are also tipped by investment banks. Based on this, I further examine the extent to which small hedge funds differ from large hedge funds in information acquisition by testing the differences of regression coefficients between large and small hedge funds. The Chi-square test results are presented in Table 2.6 Panel B. The results show that, for upgrade recommendations, the coefficient on $\Delta rec \times AR$ for large hedge funds is higher than that for small hedge funds at a 1% significance level, whereas no similar pattern is observed for downgrade recommendations. These results suggest that affiliated large hedge funds are more likely to acquire private information on upcoming upgrades than small hedge funds, but for downgrade recommendations, the chances of being tipped off are alike between large and small hedge funds.

In summary, the results suggest that the prime brokerage affiliations of hedge funds with analysts' investment banks contribute positively to the trading of hedge funds in relation to recommendation changes. Moreover, it shows that affiliated hedge funds are more likely to buy stocks on upcoming upgrades or sell stocks on upcoming downgrades. Assuming that the coefficients on the interaction of recommendation changes and affiliations proxy for the information leakage, the results support the hypothesis that hedge funds are more likely to acquire private information on forthcoming stock recommendations if they have prime brokerage relationships with analysts' investment banks.

2.5 Affiliations and abnormal returns

In this section, I compare the post-recommendation abnormal returns earned by affiliated and non-affiliated hedge funds. I then do the robustness check by testing whether the abnormal returns are determined by the characteristics of recommendations, analysts, or fund managers.

2.5.1 Abnormal returns: affiliated vs. non-affiliated hedge funds

If investment banks compete for prime brokerage businesses, I would expect that trading based on banks' private information leads to higher profits for affiliated hedge fund clients. In order to evaluate the investment values of informed trading, I focus on net-rec tradings. I define net-rec tradings as hedge fund tradings that are in the same direction as the subsequent recommendation changes. I include only hedge funds with stock holdings increased (or decrease) one or two days before the public release of upgrade (or downgrade) recommendations. The analyses are performed separately for upgrade and downgrade recommendations.

I partition the stocks held by affiliated and non-affiliated hedge funds and received recommendations from analysts into two portfolios, with each portfolio weighted by the dollar value of stock holdings of each hedge fund. The portfolios are rebalanced at the end of every quarter so that the latest fund trades are included in the portfolios at each point in time. Over the sample period, 362 tradings for upgrades and 441 tradings for downgrades are classified in the affiliated group, and 947 tradings for upgrades and 1355 tradings for downgrades are classified in the non-affiliated group, respectively.

To evaluate variations in returns earned by hedge funds, I compute the abnormal return of a stock as the difference between the stock return and the return of one of the 125 benchmark portfolios that have comparable characteristics in size, book-to-market ratio, and past stock returns (Daniel, Grinblatt, Titman, and Wermers 1997, thereafter DGTW[8]). The cumulative abnormal return (CAR) of each stock held by a hedge fund are then calculated based on d days (d=2, 30, 60, 90, 120, 150, 180, 270, and 360 days) trading windows after the recommendation release date.

Table 2.7 and Figure 2.3 present post-recommendation cumulative abnormal returns of the affiliated and non-affiliated portfolios. The average cumulative abnormal returns in d days (d=2, 30, 60, 90, 120, 150, 180, 270, and 360 days) after the recommendation release date are reported for upgrades and downgrades, respectively. In Table 2.7 Panel A, the average CARs in all time windows subsequent to upgrades are significantly positive for the affiliated portfolios, with the highest 360-day average CAR of 0.0718 and the lowest 30-day average CAR of 0.0082. However, only the 2-day average CAR for the non-affiliated portfolios is positive. Except for the 30-day window, the average post-upgrades CARs in all time windows of the affiliated portfolios are higher than those of the non-affiliated portfolios

[8]The DGTW benchmarks are available via `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`

at the 1% significance level. The test results suggest that affiliated hedge funds earn higher post-event short-term abnormal returns by buying prior to upgrades than do non-affiliated hedge funds.

Table 2.7 Panel B presents the analyses of post-downgrades average CARs of the affiliated and non-affiliated portfolios. From the 2-day to 120-day time windows, the average CARs of the affiliated portfolios are significantly lower than those of the non-affiliated portfolios at a 1% level, suggesting that the prime brokerage affiliations help hedge funds avoid negative or relatively low abnormal returns induced by the release of downgrade recommendations. For the remaining time windows, the average CARs of the affiliated portfolio show a growing pattern relative to those of the non-affiliated portfolio. These results suggest the potential profitable opportunities for the reverse tradings of hedge funds after downgrades.

I further analyze the short-term abnormal returns earned by hedge funds through informed trading based on two characteristics. The first is the reputation of the analysts issuing recommendations. A star is defined as any analyst that ranked as an All-American (first, second, third, or runner-up teams) in the annual polls in the Institutional Investor magazine. The star characteristics indicate that an analyst has a high reputation relative to others, and a recommendation issued by the star analyst could cause extensive attention in the market.

The second characteristic is the influence of recommendation changes on stock price. A recommendation change is influential if it has a significant impact on the stock price of the covered firm, as many investors adjust their holdings to the information produced by analysts. Based on Loh and Stulz (2011), I identify an influential recommendation by checking if the two-day CAR is in the same direction as the recommendation change and the absolute value of CAR exceeds $1.96 \times \sqrt{2} \times \sigma_\epsilon$, where σ_ϵ is the standard deviation of residuals from a daily time-series regression of past three-month stock returns against market returns and the Fama-French factors SMB and HML. The purpose of characteristics-based analyses is to examine the impact of prime brokerage affiliations on the abnormal returns earned by hedge funds after controlling for analyst- and recommendation-level factors.

Panel A and B in Table 2.8 provide the analyses of characteristics-based average CARs of affiliated and non-affiliated portfolios over 2 days, 30 days, 60 days, and 90 days. In the sample from 2003-2012, 8.75% of hedge fund tradings are in recommendations issued by star analysts and 17% in influential recommendations. From recommendations issued by both stars and by non-stars, the affiliated portfolios earn significantly higher average CARs and avoid significantly lower average CARs in 2-day, 60-day, and 90-day time windows than the non-affiliated portfolios[9]. The results suggest that prime brokerage affiliations with analysts' investment banks have positive impact on hedge funds' abnormal returns no matter whether the analysts are star analysts or not. A potential explanation is that analysts tend to show their favoritism to hedge funds, as hedge funds with affiliations are either important to their brokerage firms or important to their own compensation and future career[10].

In contrast, abnormal returns earned from influential and non-influential recommendations tend to differ. Relative to non-affiliated hedge funds, affiliated hedge funds earn significantly higher average CARs and avoid significantly lower average CARs in most time windows by trading prior to non-influential recommendations. However, the average CARs earned or avoided from influential recommendations appear to be comparable across two portfolios, especially for upgrades. A potential explanation is that information leakage is less likely to occur among influential recommendations as analysts tend to hide their catering behavior in the non-influential recommendations.

In summary, the above analyses suggest that affiliated hedge funds earn higher post-recommendation abnormal returns by buying prior to upgrades and avoid lower post-recommendation

[9] All upgraded recommendations issued by star analysts in the sample are in the affiliated portfolio, which indirectly provides evidence that affiliated hedge funds earn higher short-term abnormal returns than non-affiliated hedge funds (see Loh and Stulz (2011))

[10] Concerned about their compensation and career prospects, analysts are motivated to leak private information to their hedge fund clients as they attempt to win broker votes (see Maber (2014)) or the votes for All-America analysts from hedge funds.

abnormal returns by selling prior to downgrades than do non-affiliated hedge funds. Test results are consistent with the hypothesis that hedge funds with prime brokerage affiliations with analysts' employer are more likely to acquire profitable information on future stock recommendations from the analysts. Investment banks play an important role in providing profitable opportunities for hedge funds to buy (or sell) prior to upgrades (or downgrades) even after controlling for star analysts and influential recommendations.

2.5.2 Affiliations or skills?

I check the robustness of the results by testing whether affiliated hedge funds are more likely to invest in stocks that analysts issue profitable recommendations. If affiliated hedge funds have better stock picking and timing skills, would information be transmitted the other way around from hedge funds to analysts? Specifically, I examine whether the relatively high abnormal returns earned by affiliated hedge funds are determined by managers' skills in getting information from sources other than investment banks.

I examine hedge fund managers' skills based on fund alphas and compare them across the affiliated and non-affiliated portfolios. I estimate alpha of an individual hedge fund by adopting a rolling-window method to regress the net-of-fee monthly excess return (in excess of risk-free rate) of each hedge fund on the seven factors constructed by Fung and Hsieh (2004). The seven factors include the S&P 500 monthly return minus risk free rate, Russell 2000 index monthly return minus S&P 500 monthly return, change in the 10-year treasury constant maturity yield, change in the Moody's Baa yield less 10-year treasury constant maturity yield, the return of bond primitive trend-following strategy, the return of currency primitive trend following strategy, and the return of commodity primitive trend-following strategy. Following Naik, Ramadorai, and Stromqvist (2007), for each month, I calculate a fund's factor loadings of the seven factors using the previous 24 months of data, and obtain the risk-adjusted return as the fund's alpha. A fund company's alpha is calculated as the average alphas of the managed hedge funds in the same company.

In the unreported results, the average alpha is 1.33% for large hedge funds and 1.11% for small hedge funds. The alphas are comparable across affiliated and non-affiliated hedge funds, either large or small, suggesting that affiliated hedge funds are not more skillful in equity tradings than non-affiliated hedge funds.

Table 2.9 presents the analyses of post-recommendation cumulative abnormal returns of affiliated and non-affiliated portfolios by controlling for managers' alphas. I separately sort large and small hedge funds into three terciles based on fund's alpha in a quarter, with the top and bottom terciles defined as high alpha and low alpha hedge funds, respectively. I test the differences of CARs over 2-day, 30-day, 60-day, and 90-day windows between affiliated and non-affiliated portfolios for the high alpha and low alpha hedge funds, respectively. If the affiliated and non-affiliated hedge funds with comparable skills show differences in abnormal returns, the disparities are likely to be from the "hidden" skills or affiliation-driven skills of hedge funds.

I find that, in the high alpha hedge fund group, the post-upgrade (or post-downgrade) CARs of affiliated portfolio are significantly higher (or lower) than those of non-affiliated portfolio in most of the reported time windows. However, the similar difference pattern only exists in the 2-day window in the low alpha group. The results of robustness tests support the hypotheses after controlling for hedge fund managers' skills. Hedge funds benefit from the prime brokerage affiliations with analysts' investment banks by investing in stocks that analysts issue profitable recommendations.

I also find that, only in the affiliated portfolios, the highly-skilled hedge funds display superiority in earning higher post-upgrade abnormal returns or avoid lower post-downgrade abnormal returns, relative to the less-skilled hedge funds. These results indicate that hedge fund skills in stock investments can be realized only in an informed environment, and private information plays an important role in making difference in the equity trading skills of hedge funds. These results also suggest that investment banks tend to cater to hedge funds with high skills by providing them with more profitable opportunities, in expectation of higher rewards in the future.

2.5.3 Hedge fund risk exposure

So far I have shown the beneficial impact of investment banks on hedge fund equity investments by examining the short-term stock abnormal returns. A concern I address here is the extent to which values are added to hedge funds through informed tradings. Sharpe (1992) shows that an asset class factor model can be used to determine how effectively individual fund managers have allocated the overall assets and achieved performance target through active management. The funds' risk/reward characteristics can be captured by taking on risk exposures on certain factors, with the weights estimated by regressing individual fund returns on the risk factors (Hasanhodzica and Lo (2006)). Accordingly, I use a linear factor model to examine the exposure of hedge fund returns to recommendation changes. If hedge funds with prime brokerage affiliations have priority in acquiring information on analysts' recommendations, I anticipate that these hedge funds have higher exposure to the stock recommendation changes with large market reactions.

I perform the analysis by constructing recommendation factors for hedge funds and examining the allocation of hedge funds' portfolios among recommendation-oriented asset classes. I focus on hedge funds that earn immediate positive two-day abnormal returns by buying upgrades and avoid immediate negative two-day abnormal returns by selling downgrades prior to the recommendation release. For a hedge fund, the immediate profits earned (or the losses avoided) in each share of stock is the two-day CAR (or -CAR) of an analyst recommendation. I use the earned profits to denote the immediate positive profits earned and the immediate negative losses avoided by hedge funds in the following text. To compare the investment values of affiliated and non-affiliated hedge funds effectively, I choose 3 stocks with the highest earned profits out of those invested by affiliated hedge funds and 3 stocks with the highest earned profits out of those invested by non-affiliated hedge funds. I put each stock into one of the six barrels that belong to two different groups and rank the stocks by earned profits from high to low in each group. I refer to the time-series stock returns in each barrel as a recommendation factor.

I perform a time-series regression of hedge funds' monthly returns on the recommendation factors and the Fama-French-Carhart four factors.

$$R_{it} = \sum_{k=1}^{3} \beta_{ik}\ A.\ RecFactor_{kt} + \sum_{k=1}^{3} \gamma_{ik}\ NA.\ RecFactor_{kt} \\ + \delta_1 MKT_t + \delta_2 SMB_t + \delta_3 HML_t + \delta_4 MOM_t + \epsilon_{it} \tag{2.5}$$

where $A.\ RecFactor_{kt}$ is the recommendation factor k in the affiliated group in month t, $NA.\ RecFactor_{kt}$ is the recommendation factor k in the non-affiliated group in month t, R_{it} is the return of hedge fund i in month t, and MKT_t, SMB_t, HML_t, and MOM_t are the Fama-French-Carhart four factors, respectively. β_{ik} and γ_{ik} are factor loadings on recommendation factor k in the affiliated and non-affiliated groups, respectively, which reflect the extent to which hedge fund returns are exposed to the recommendation changes.

Table 2.10 shows the analyses of hedge funds' exposure to analysts' recommendation changes. The results are presented separately for large and small hedge funds. From $k = 1$ to 3, the mean and median factor loadings β_{ik}s in the affiliated groups, either large or small, are larger than the mean and median γ_{ik}s in the non-affiliated group at 1% significance level. These results suggest that, relative to non-affiliated hedge funds, significantly larger proportion of funds' returns in the affiliated group is attributable to recommendation changes. As affiliated hedge funds do not have superior skills in stock trading, the higher exposure of their returns to recommendation changes is consistent with the hypothesis that hedge funds with prime brokerage affiliations are more likely to acquire private information on future analysts' recommendations.

Even the most intentional catering behavior can be unhelpful to hedge funds if the recommendation change does not move the stock price. In the unreported test, I construct recommendation factors by choosing 3 stocks with the lowest profits out of those invested by hedge funds in affiliated and non-affiliated groups, respectively, and test the weights on the recommendation factors in two groups through regression analyses. I find that the factor loadings are comparable across affiliated and non-affiliated groups for both large and small hedge funds.

The exposure analysis provide evidence that prime brokerage affiliations with analysts' investment banks add values to hedge funds by providing them with profitable investment opportunities. Investment banks offer benefits to hedge funds in addition to the prime brokerage services they meant to provide, in order to attract customers and boost their competitiveness in the prime businesses.

2.6 Conclusions

The paper examines the channel through which hedge funds obtain private information on analysts' recommendations by testing their trading behaviors before public release of analysts' reports. Empirical results provide strong support for the importance of prime brokerage affiliations on information acquisition of hedge funds. First, I find that affiliated hedge funds tend to buy (or sell) stocks one or two days before the public release of upgrade (or downgrade) recommendations. Second, affiliated large hedge funds tend to buy upgrades and sell downgrades in a larger magnitude compare to non-affiliated hedge funds. Third, affiliated hedge funds have a higher probability to trade in a way that is consistent with upcoming recommendation changes than non-affiliated hedge funds. Fourth, affiliated hedge funds earn higher (or avoid lower) short-term abnormal returns by buying (or selling) before upgrades (or downgrades) than non-affiliated hedge funds.

I show that, although affiliated large hedge funds have a higher (or lower) average pre-release demands for upgrades (or downgrades) than non-affiliated hedge funds, the same differences have not been observed in the post-recommendation tradings. Nor do I see a difference in the magnitude of tradings between affiliated and non-affiliated small hedge funds. Nevertheless, I find that small hedge funds appear to acquire private information from analysts' investment banks, as the probability that affiliated small funds trade ahead in the same direction as subsequent recommendation changes is higher compared to that of non-affiliated funds.

The results are robust after controlling for the characteristics of analysts and recommendations. I also test an alternative explanation that affiliated hedge funds are skillful enough to invest in stocks that analysts issue profitable recommendations. The test results do not bear out this explanation by showing that disparities of abnormal returns between affiliated and non-affiliated hedge funds still exist even after controlling for fund managers' alphas.

Some caveats should be noted in regards to the interpretation of my findings. First, data limitations do not allow me to estimate the quantitative benefits of leaking information to hedge funds. As a result, I am unable to build a direct connection between hedge fund tradings and investment bank revenues from prime brokerage business. The classification of large and small hedge funds alleviates this concern to some extent, as prime brokerage fees are likely positively related to the size of investors. Second, an alternative potential explanation for trading ahead is the analysts' optimistic reporting. According to Bilinsky, Cumming, and Hass (2014) and Chung and Teo (2012), analysts cater to hedge funds by issuing optimistic research reports, so that hedge funds can make profits by trading ahead in the same direction as the reports. The information leakage assertion does not disconfirming theirs, as both arguments can coexist and share the same purposes. However, analyst reports are likely to be determined by various factors in addition to the catering behaviors, and lacking of comprehensive empirical analyses makes the explanation relatively weak. In conclusion, the results provide strong evidence on the importance of investment banks in setting up information channels between hedge funds and analysts.

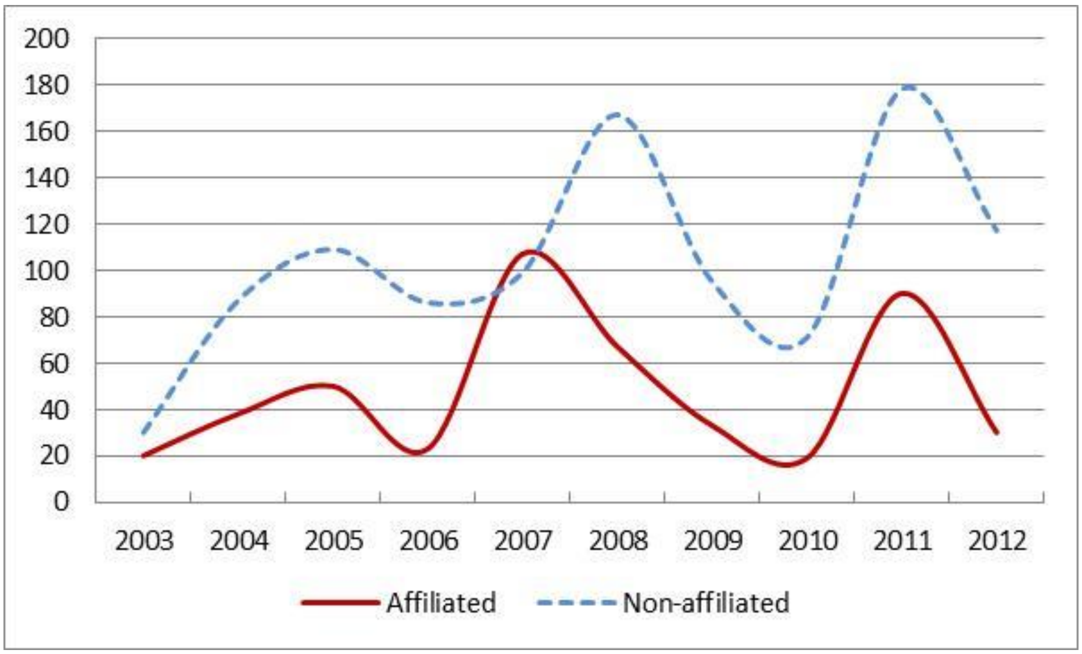


Figure 2.1: The cumulative hedge fund tradings: affiliated vs non-affiliated

The figure plots the number of cumulative tradings prior to recommendation changes of affiliate and non-affiliated hedge funds by years. Affiliated hedge funds are hedge funds that use reporting analysts' investment banks as their prime brokers. The remaining funds are non-affiliated hedge funds.

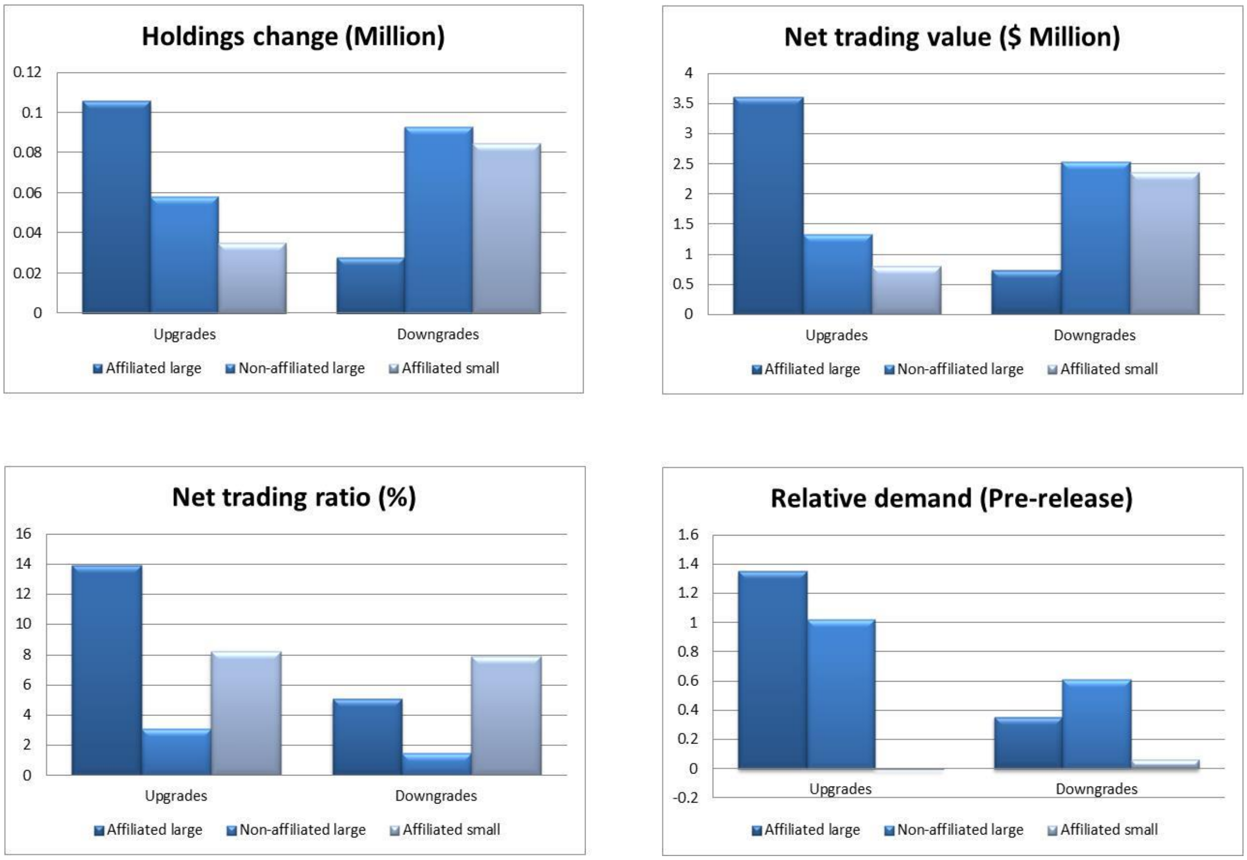
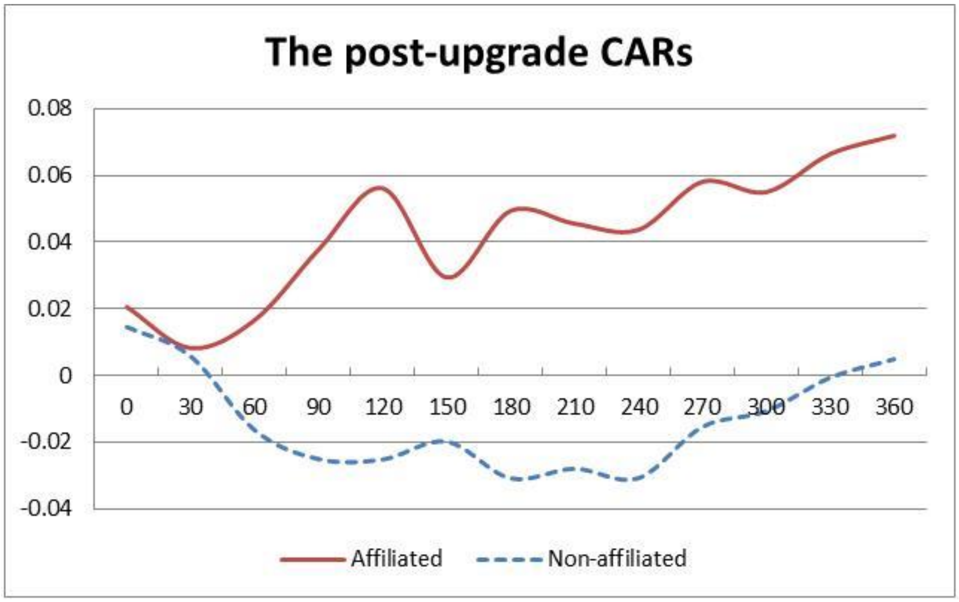


Figure 2.2: The measures of hedge fund trading activities

The figure plots the averages of hedge fund tradings for two different fund groups: affiliated and non-affiliated. The measures of hedge fund trading activities include holdings change, net trading value, net trading ratio, and pre-release relative demand, which are defined in Section 4.1 and 4.2. Affiliated hedge funds are hedge funds that use reporting analysts' investment banks as their prime brokers. The remaining funds are non-affiliated hedge funds. Hedge funds with asset under management no less than $1 billion are defined as large hedge funds, and small hedge funds otherwise.



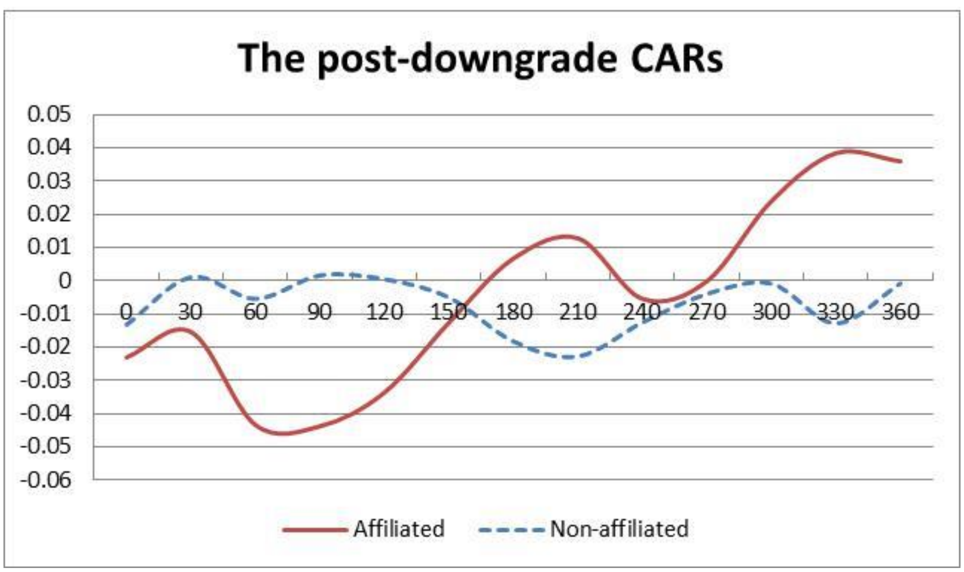


Figure 2.3: The post-recommendation CARs: affiliated vs. non-affiliated portfolios

The figures plot the post-recommendation cumulative abnormal returns of stocks invested by affiliate and non-affiliated hedge funds, with the top one for upgrades and the bottom one for downgrades. Affiliated hedge funds are hedge funds that use reporting analysts' investment banks as their prime brokers. The remaining funds are non-affiliated hedge funds.

Table 2.1: Summary statistics of recommendation changes and hedge fund tradings

This table presents summary statistics of recommendation changes and hedge fund tradings. The recommendation change data are from I/B/E/S detail file matched with 13F institutional holding data and TASS hedge fund database from 2003 to 2012. Panel A shows the distribution of recommendation changes in the sample. Panel B shows the cumulative number of recommendation changes over years. Panel C shows the descriptive statistics for hedge fund tradings in recommended stocks, where Net-rec refers to hedge funds that trade in the same direction as recommendation changes, and Net-rec I refers to subsamples of Net-rec in which hedge fund tradings have different signs than those of stock abnormal returns in the corresponding month. Panel D shows the summary statistics for regression variables.

Panel A: recommendation change frequencies

Change in recommendations	Frequency	Percent	Cumulative Frequency	Cumulative Percent
-4	3	0.08	3	0.08
-3	16	0.43	19	0.51
-2	816	22.07	835	22.58
-1	961	25.99	1796	48.57
0	593	16.04	2389	64.60
1	776	20.98	3165	85.59
2	533	14.41	3698	100
3	0	0	3698	100
4	0	0	3698	100

Panel B: cumulative recommendation changes

	Total	Upgrades	Downgrades	No change
2003	192	60	74	58
2004	506	205	248	53
2005	475	142	206	127
2006	388	108	259	21
2007	421	97	204	120
2008	442	197	179	66
2009	266	92	133	41
2010	173	70	96	7
2011	502	218	214	70
2012	333	120	183	30
Average	370	131	180	59

Table 1 - continued

Panel C: descriptive statistics

	Total	Upgrades	Downgrades	NoChg	Net-rec	Net-rec I
All separate recommendation change samples						
Num of firms	539					
Num of investment banks	11					
Num of analysts	550					
Num of star analysts	25					
Num of rec changes	750	273	374	103	571	273
Num of affiliated recs	177	62	70	45	148	64
Num of non-affiliated recs	573	211	304	58	423	209
Num of influential recs	136	55	81	0	105	50
Num of non-influential recs	614	218	293	103	466	223
All hedge fund samples						
Num of hedge funds	176					
Num of hedge fund tradings	3698	1309	1796	593	1460	652
Affiliated tradings	1130	362	441	327	417	182
Non-affiliated tradings	2568	947	1355	266	1043	470
Large hedge fund samples						
Num of hedge funds	59					
Num of hedge fund tradings	1599	581	758	260	645	279
Affiliated tradings	504	172	192	140	196	87
Non-affiliated tradings	1095	409	566	120	449	192
Small hedge fund samples						
Num of hedge funds	117					
Num of hedge fund tradings	2099	728	1038	333	815	373
Affiliated tradings	626	190	249	187	221	95
Non-affiliated tradings	1473	538	789	146	594	278

Panel D: summary statistics for regression variables

	N	Mean	Median	Std Dev	Min	Max
Analyst experience (yrs)	3698	2.409	2	3.164	0	17
Coverage	3698	5.392	5	3.052	1	22
Ln MV ($ million)	3559	3.846	3.881	0.701	1.790	5.549
Stock return (qtrly)	3635	0.021	0.021	0.198	-0.670	1.296
Stock turnover (qtrly)	3635	0.846	0.681	0.642	0.055	4.067
Hedge fund AUM (million)	3612	18.598	18.739	1.509	11.512	23.083
Hedge fund return (qtrly)	3509	0.0183	0.019	0.089	-0.609	0.744
Hedge fund flow (qtrly)	3612	0.146	0.000	2.998	-1.032	69.051
Hedge fund age (months)	3612	84.095	61.026	68.297	0	310.614

Table 2.2: Statistical analysis of affiliated vs. non-affiliated trading

This table presents statistical analysis for the trading of affiliated and non-affiliated hedge funds prior to the release of recommendations. Hedge fund tradings are measured through holdings change, net trading value, and net trading ratio for upgrades (Panel A) and downgrades (Panel B), respectively. The last four columns test the mean differences, with t-values in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: upgrades

	Large hedge funds		Small hedge funds		Mean difference / t-value			
	Affiliated (1)	Non-aff. (2)	Affiliated (3)	Non-aff. (4)	(1)-(2)	(3)-(4)	(1)-(3)	(3)-(2)
Holdings change (Million)								
Mean	0.106	0.058	0.035	0.053	0.048**	-0.018	0.069***	-0.023
Median	0.017	0.007	0.004	0.005	(2.25)	(-1.06)	(2.67)	(-0.31)
Min	-0.314	-0.201	-0.525	-0.524				
Max	0.973	0.650	0.892	0.709				
Net trading value ($ Million)								
Mean	3.607	1.334	0.799	1.256	2.273***	-0.457	2.637***	-0.243
Median	0.389	0.129	0.126	0.149	(2.85)	(-0.58)	(3.28)	(-0.73)
Min	-41.075	-21.522	-70.072	-30.651				
Max	44.598	24.405	48.099	48.873				
Net trading ratio (%)								
Mean	13.876	3.097	8.175	3.134	10.780***	5.041***	2.265*	5.078***
Median	9.918	2.469	6.981	2.174	(6.94)	(5.52)	(1.76)	(5.26)
Min	0	0	0	0				
Max	66.667	11.428	28.571	12.001				

Panel B: downgrades

	Large hedge funds		Small hedge funds		Mean difference / t-value			
	Affiliated (1)	Non-aff. (2)	Affiliated (3)	Non-aff. (4)	(1)-(2)	(3)-(4)	(1)-(3)	(3)-(2)
Holdings change (Million)								
Mean	0.028	0.093	0.085	0.040	-0.064**	0.045	-0.051**	-0.008
Median	0.067	0.010	0.003	0.003	(-2.21)	(1.36)	(-2.20)	(-0.28)
Min	-0.893	-0.954	-2.011	-2.779				
Max	1.652	2.364	2.983	2.979				
Net trading value ($ Million)								
Mean	0.733	2.538	2.354	0.942	-1.805**	1.412**	-1.198**	-0.702
Median	0.222	0.333	0.122	0.117	(-2.07)	(2.20)	(-2.02)	(-0.39)
Min	-30.091	-17.130	-25.381	-30.641				
Max	33.856	61.259	38.204	35.168				
Net trading ratio (%)								
Mean	5.051	1.450	7.856	1.841	3.601***	6.015***	-0.404	6.406***
Median	2.941	0.855	8.088	1.138	(6.19)	(7.80)	(-0.47)	(4.58)
Min	0	0	0	0				
Max	22.222	9.524	30.769	10.526				

Table 2.3: Pre- and Post-release relative trading demands

This table presents the statistics of relative trading demand of affiliated and non-affiliated hedge funds prior to (pre) and subsequent to (post) the release of analyst recommendation changes. Relative trading demand is calculated as the percentage change in aggregate holdings of a stock in a quarter by hedge funds, relative to other institutional investors. Panel A and B present the relative trading demand for upgrade and downgrade recommendations, respectively. The last four columns test the mean and median differences between the two groups using paired t-test and Wilcoxon rank-sum test, respectively. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: upgrades

	Relative demand							
	Affiliated		Non-affiliated		Difference test			
					t-value		Wilcoxon p-val	
	Pre (1)	Post (2)	Pre (3)	Post (4)	(1)-(2)	(3)-(4)	(1)-(3)	(2)-(4)
Large hedge funds								
Mean	1.350	0.035	1.019	0.034	(2.76)	(2.61)	(0.0238)	(0.307)
Median	0.252	-0.002	0.049	-0.007	***	**	**	
Min	-0.563	-0.472	-0.563	-0.521				
Max	7.486	0.819	7.547	0.616				
INST mean	0.038	0.008	0.038	0.008				
Small hedge funds								
Mean	-0.008	0.083	0.005	0.022	(-0.71)	(1.08)	(0.438)	(0.0643)
Median	0.048	0.018	-0.051	-0.005				*
Min	-0.418	-0.178	-0.419	-0.303				
Max	0.685	0.432	0.689	0.510				
INST mean	0.137	-0.001	0.137	-0.001				

Panel B: downgrades

	Relative demand							
	Affiliated		Non-affiliated		Difference test			
					t-value		Wilcoxon p-val	
	Pre (1)	Post (2)	Pre (3)	Post (4)	(1)-(2)	(3)-(4)	(1)-(3)	(2)-(4)
Large hedge funds								
Mean	0.355	0.060	0.610	0.107	(0.83)	(3.1)	(0.0476)	(0.166)
Median	-0.022	0.002	0.055	0.034		***	**	
Min	-0.563	-0.472	-0.578	-0.472				
Max	3.401	0.819	3.527	0.861				
INST mean	0.050	0.005	0.050	0.005				
Small hedge funds								
Mean	0.063	0.053	0.015	0.039	(0.38)	(-0.22)	(0.408)	(0.523)
Median	-0.013	0.025	-0.043	0.009				
Min	-0.405	-0.296	-0.405	-0.296				
Max	0.744	0.479	0.850	0.496				
INST mean	0.127	0.008	0.127	0.008				

Table 2.4: The timing of hedge fund tradings prior to recommendation changes

This table presents the timing of affiliated and non-affiliated hedge fund trading by regressing stock holdings changes in quarter t on subsequent recommendation changes. Following Klein, Saunders, and Wong (2014), the estimated regression is: $\Delta share_{j,i,t} = \alpha_k + \beta_k \Delta rec_{i,d} + \epsilon_{i,k}$, where $\Delta share_{j,i,t}$ is the change in the number of shares held by hedge fund j in stock i during quarter t, and $\Delta rec_{i,d}$ is the change of an analyst's recommendation for stock i issued on day d ($d = t + k,\ k = 1, 2, ...,\ 10\ day(s)$). Ups and Downs refer to the samples that are associated with non-negative and non-positive recommendation changes, respectively. Standard errors are two-way clustered by hedge funds and investment banks. Yearly fixed effects are included. This table reports the estimated coefficients for affiliated and non-affiliated hedge fund trading from 2003 to 2012. T-values are presented in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Day d = Form 13F	β_k from regression $\Delta share_{j,i,t} = \alpha_k + \beta_k \Delta rec_{i,d} + \epsilon_{i,k}$					
quarter-end	Affiliated			Non-affiliated		
$t + k$ day(s)	Ups & Downs	Ups	Downs	Ups & Downs	Ups	Downs
($k = 1, 2, ..., 10$)	(1)	(2)	(3)	(4)	(5)	(6)
$d = t + 1$	0.013*	0.059**	0.036*	0.006	-0.011	-0.037
	(1.76)	(2.21)	(1.72)	(0.73)	(-0.28)	(-0.93)
$d = t + 2$	0.021***	0.030***	0.068**†	0.001	-0.014	-0.008
	(7.21)	(3.89)	(2.10)	(0.21)	(-0.59)	(-0.62)
$d = t + 3$	0.015	0.017*	0.001	0.007	0.003	0.012
	(0.91)	(1.68)	(0.05)	(1.26)	(0.18)	(0.92)
$d = t + 4$	0.010	0.025	0.005	0.001	0.021	-0.013
	(1.02)	(1.15)	(0.58)	(0.12)	(0.94)	(-0.54)
$d = t + 5$	0.121	0.012	-0.017	-0.004	-0.025	0.014
	(1.17)	(0.85)	(-1.00)	(0.46)	(-0.71)	(0.36)
$d = t + 6$	-0.005	-0.006	-0.258	0.004	0.001	0.006
to $t + 10$	(-0.37)	(-0.24)	(-1.25)	(1.29)	(0.15)	(1.35)

† - Large hedge funds only.

Table 2.5: Regression analyses of hedge fund trading prior to recommendation changes

This table presents the regression analyses of hedge fund trading prior to recommendation changes. I line up hedge fund holdings reported at quarter-end date t in Form 13F with analyst recommendations released on days d ($d = t+1$ or $t+2$). The dependent variable is hedge fund trading, which is measured through $\Delta shares$ and $\$\Delta shares$ for a stock during quarter t. Independent variables are as follows: Δrec is the change of an analyst's recommendation for a stock released on day d. AL, NAL, and AS are dummy variables indicating the affiliated large hedge funds, non-affiliated large hedge funds, and affiliated small hedge funds, respectively. Three interaction variables are included: $\Delta rec \times AL$, $\Delta rec \times NAL$, and $\Delta rec \times AS$. *Ana exp* is analyst experience calculated as the number of quarters since an analyst issued the first recommendation on I/B/E/S. *Coverage* is the number of analysts that issued at least one recommendation for a firm over a quarter. *Ln MV* is the logarithm of the firm's market value at last fiscal year-end. *Stk return* is the return of a stock over last quarter. *Stk turnover* is the turnover of a stock over last quarter. HF *return* is the quarterly rate of return of a hedge fund company, calculated as the percentage change of net asset values of a fund company between the beginning and the end of last quarter. HF *flow* is the quarterly flow of a hedge fund company, calculated as the percentage change of AUMs of a fund company between the beginning and the end of a quarter. HF *age* the age of a hedge fund company, calculated as the asset weighted average age (in months) of the managed hedge funds. Panel A presents the regression analyses of using two different measures as dependent variables, with column (1) and (4) show the results for total samples, column (2) and (5) for non-negative recommendation changes, and column (3) and (6) for non-positive recommendation changes. Panel B presents the F-stats of equality tests between regression coefficients of the two regressions. Panel C presents the regression analysis of large hedge funds, with Net-rec in column (2) and (5) refers to the hedge funds that trade in the same direction as recommendation changes and Net-rec I in column (3) and (6) refers to the subsamples of Net-recs that have different signs than those of the corresponding monthly stock abnormal returns. Yearly fixed effects are included. Standard errors are two-way clustered by hedge funds and investment banks. The table reports the estimated coefficients for the entire period from 2003 to 2012. The last three rows report the number of observations, the adjusted R^2, and the F-tests results of each regression. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: regression analysis

	Δshares (Million)						\$$\Delta$shares (Million)					
	Total (1)	t-val	Ups (2)	t-val	Downs (3)	t-val	Total (4)	t-val	Ups (5)	t-val	Downs (6)	t-val
Δrec	0.025	0.36	-0.009	-0.73	-0.002	-0.42	0.074	0.64	0.034	0.10	-0.082	-0.20
AL	0.024	0.97	-0.005	-0.27	0.022	1.49	1.005	1.52	1.153	1.15	0.843	1.09
AS	-0.006	-0.35	-0.037**	-2.59	-0.010	-0.97	-0.093	-0.28	-0.507	-0.76	-0.747	-1.52
NAL	0.016	0.67	0.016	0.73	0.002	0.10	0.437	0.77	0.799	0.94	-0.539	-0.61
$\Delta rec \times AL$	0.025***	3.51	0.050***	2.81	0.025***	2.85	0.723***	3.94	0.472	1.49	1.218**	2.49
$\Delta rec \times AS$	-0.021**	-2.25	0.002	0.05	-0.021*	-1.93	-0.727***	-3.31	-0.546	-1.06	-0.806*	-1.92
$\Delta rec \times NAL$	0.006	0.54	0.006	0.58	-0.001	-0.16	0.065	0.20	-0.138	-0.56	-0.232	-0.60
Ana exp	-0.0006	-0.55	-0.0003	-0.31	0.0002	0.01	-0.005	-0.14	-0.036	-0.74	-0.003	-0.06
Coverage	0.002	1.07	0.0025	0.70	-0.0007	-0.29	0.025	0.29	0.126	0.98	-0.023	-0.28
ln MV	0.006	0.75	0.017*	1.80	0.009	0.85	0.491*	1.78	0.621**	2.05	0.935**	2.54
Stk return	0.007	0.39	0.022	0.71	-0.001	-0.08	0.769	1.06	1.205	1.06	1.068	1.40
Stk turnover	-0.001	-0.11	-0.007	-0.81	0.011	0.77	-0.139	-0.43	-0.257	-0.53	0.293	0.73
HF return	-0.027	-0.38	-0.033	-0.53	-0.050	-0.58	-0.658	-0.34	-1.879	-1.04	-3.083	-0.94
HF flow	0.0007	0.39	0.001	0.04	0.002	0.08	0.031	0.04	0.035	0.10	0.073	0.07
HF age	0.0001	0.49	0.0001	0.74	-0.00003	-0.69	0.001	0.32	0.003	0.63	-0.004	-1.32
Constant	-0.0209	-0.49	-0.072	-1.35	0.001	0.02	-1.293	-1.25	-2.30**	-1.99	-1.661	-1.32
Yearly fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by HF	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by IB	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	3698		1902		2389		3698		1902		2389	
R-square	0.0252		0.0465		0.0253		0.0372		0.0631		0.0229	
F Statistic	6.70		6.17		17.54		11.10		14.73		22.42	

Table 5 - continued

Panel B: equality tests between regression coefficients (F-stats)

	Δshares (Million)						$Δshares (Million)					
	Total (1)		Ups (2)		Downs (3)		Total (4)		Ups (5)		Downs (6)	
$\Delta rec \times AL - \Delta rec \times NAL$	8.62	***	18.97	***	12.67	***	11.00	***	0.94		21.66	***
$\Delta rec \times AL - \Delta rec \times AS$	40.82	***	5.30	**	186.86	***	34.75	***	4.02	**	42.96	***
$\Delta rec \times NAL - \Delta rec \times AS$	4.65	**	0.03		3.85	*	6.17	**	0.08		9.56	***

Panel C: regression analysis of large hedge funds: upgrades & downgrades

	Δshares (Million)						$Δshares (Million)					
	Total (1)	t-val	Net-rec (2)	t-val	Net-rec I (3)	t-val	Total (4)	t-val	Net-rec (5)	t-val	Net-rec I (6)	t-val
Δrec	0.006	0.90	0.073***	3.29	0.038***	3.75	0.091	0.24	1.899***	3.91	1.453**	2.08
AL	-0.002	-0.13	-0.001	-0.03	0.018*	1.89	0.146	0.33	0.691	0.17	1.300	2.08
$\Delta rec \times AL$	0.022**	3.01	0.062**	2.09	0.033	1.41	0.844***	3.22	2.441**	2.19	1.307	1.06
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
Yearly fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by HF	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by IB	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1599		645		404		1599		645		404	
R-square	0.0591		0.3426		0.2956		0.0587		0.3797		0.2808	
F Statistic	5.82		9.82		11.78		6.77		11.00		4.38	

Table 5 - continued

Panel D: regression analysis of large hedge funds: upgrades

	Δshares (Million)						$Δshares (Million)					
	Total (1)	t-val	Net-rec (2)	t-val	Net-rec I (3)	t-val	Total (4)	t-val	Net-rec (5)	t-val	Net-rec I (6)	t-val
Δrec	-0.001	-0.07	0.031	0.82	-0.013	-0.41	-0.167	-0.19	1.455	1.66	-0.508	-0.30
AL	-0.030**	-2.66	-0.071	-1.22	0.019	1.35	-0.036	-0.06	-2.313	-1.56	1.467	1.19
$\Delta rec \times AL$	0.046***	4.14	0.097*	1.74	-0.004	-0.19	0.708*	1.73	3.285*	1.84	-0.966	-0.72
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
Yearly fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by HF	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by IB	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	581		280		121		581		280		121	
R-square	0.0747		0.1911		0.1835		0.1034		0.2340		0.2559	
F Statistic	3.27		7.81		2.08		8.94		7.89		2.39	

Panel E: regression analysis of large hedge funds: downgrades

	Δshares (Million)						$Δshares (Million)					
	Total (1)	t-val	Net-rec (2)	t-val	Net-rec I (3)	t-val	Total (4)	t-val	Net-rec (5)	t-val	Net-rec I (6)	t-val
Δrec	0.006	0.90	0.013	0.34	0.068	1.62	-0.052	-0.11	0.532	0.26	2.123	1.53
AL	-0.002	-0.13	0.067	0.71	0.029	1.43	0.840**	2.21	2.132	0.66	3.539**	2.00
$\Delta rec \times AL$	0.022**	3.01	0.066	1.10	0.068*	1.82	1.067**	2.02	1.641	0.71	4.825***	5.20
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
Yearly fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by HF	Yes		Yes		Yes		Yes		Yes		Yes	
SE clustered by IB	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	758		365		158		758		365		158	
R-square	0.0591		0.1535		0.4633		0.0488		0.1921		0.4645	
F Statistic	5.82		2.19		7.57		2.42		2.16		7.66	

Table 2.6: Regression analyses of hedge fund trading on stock level

This table presents stock-level regression analysis of hedge fund trading prior to recommendation changes. I use Seemingly Unrelated Regressions (SUR) to estimated a system of four equations. The dependent variables are NTR_L and NTR_S, which are net trading ratio (NTR) of the stocks traded by large and small hedge funds, respectively. Independent variables include Δrec, which is the change of an analyst's recommendation for a stock issued up to two days following 13F report date, AR is a dummy variable indicating whether a stock receives at least one affiliated recommendations, $\Delta rec \times AR$ is an interaction variable of Δrec and $Affiliated$, *Ana exp* is analyst experience calculated as the number of quarters since an analyst issued the first recommendation on I/B/E/S, *Coverage* is the number of analysts that issued at least one recommendation for a firm over a quarter, *Ln MV* is the log of the firm's market value at last fiscal year-end, *Stkreturn* is the return of a stock over last quarter, and *Stkturnover* is the turnover of a stock over last quarter. Panel A presents the regression analyses of upgrades and downgrades, respectively. Panel B shows the corresponding equality tests between estimated coefficients on $\Delta rec \times AR$ and Δrec. Z-values and χ^2 statistics for regression analyses and equality tests are reported. The last three rows in Panel A report the number of observations, the adjusted R^2, and the F-tests results of each regression. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: regression analysis

	Upgrades				Downgrades			
	NTR_L (1)	z-val	NTR_S (2)	z-val	NTR_L (3)	z-val	NTR_S (4)	z-val
Δrec	0.509**	2.39	0.819***	3.94	-0.551***	-3.93	-0.476***	-2.83
$Affiliated$	0.064	0.08	1.186*	1.88	1.260**	2.22	1.303**	2.20
$\Delta rec \times Affiliated$	5.505***	5.36	1.828**	2.21	-1.562**	-2.45	-1.916***	-3.19
$Ana\ exp$	0.013	0.16	-0.019	-0.25	-0.048	-0.89	0.003	0.07
$Coverage$	0.208**	1.97	0.038	0.34	0.153*	1.88	0.250**	2.19
$ln\ MV$	0.726	1.64	1.566***	4.37	0.995***	3.15	1.151***	4.05
$Stk\ return$	0.555	0.72	-0.206	-0.26	0.224	0.27	0.847	1.19
$Stk\ turnover$	-0.213	-0.67	0.410	0.72	-0.182	-0.43	-0.914**	-2.29
$Constant$	3.268***	8.26	2.643***	16.09	2.291***	14.76	2.325***	13.57
Yearly fixed effects	Yes		Yes		Yes		Yes	
SE clustered by stock	Yes		Yes		Yes		Yes	
Observations	273		273		374		374	
Adj r-square	0.2426		0.1957		0.2169		0.2806	
F Statistic	14.13		10.98		15.47		21.38	

Panel B: equality tests

Difference between regression coefficients	Upgrades			Downgrades	
$NTR\_L - NTR\_S$	χ^2	p-val		χ^2	p-val
$NTR\_L\ (\Delta rec \times Affiliated) - NTR\_S\ (\Delta rec \times Affiliated)$	10.73	0.0011	***	0.30	0.5812
$NTR\_L\ (\Delta rec) - NTR\_S\ (\Delta rec)$	1.57	0.2109		0.13	0.7190

Table 2.7: The post-recommendation CARs of stocks invested by the affiliated and non-affiliated hedge funds

This table presents the post-recommendation cumulative abnormal returns (CARs) the affiliated and non-affiliated portfolios. I include only hedge fund tradings that are in the same direction as recommendation changes. For each recommendation change, I calculate the abnormal return for a stock as the difference between the stock return and the return of one of 125 benchmark portfolios that have comparable characteristics in size, book-to-market ratio, and past stock returns (DGTW, 1997). The cumulative abnormal returns in d days (d=2, 30, 60, 90, 120, 150, 180, 270, and 360 days) after recommendation release are reported. The sample mean, t-statistics (in parenthesis), and mean difference are presented for the affiliated and non-affiliated portfolios. Panel A and Panel B present the results for upgrade and downgrade recommendations, respectively. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: upgrades

	The post-recommendation cumulative abnormal returns (CARs)								
	2 days	30 days	60 days	90 days	120 days	150 days	180 days	270 days	360 days
Affiliated	0.0206	0.0082	0.0166	0.0377	0.0561	0.0293	0.0493	0.0580	0.0718
	(14.99)	(1.92)	(2.52)	(4.31)	(4.91)	(2.13)	(3.09)	(4.00)	(4.12)
Non-affiliated	0.0146	0.0058	-0.0163	-0.0249	-0.0251	-0.0197	-0.0307	-0.0153	0.0049
	(17.59)	(1.27)	(-2.86)	(-3.43)	(-3.07)	(-2.25)	(-3.26)	(-1.46)	(0.44)
Affiliated - Non-affiliated	0.006***	0.002	0.033***	0.063***	0.081***	0.049***	0.08***	0.073***	0.067***
	(3.72)	(0.31)	(3.22)	(4.76)	(5.34)	(2.93)	(4.37)	(3.77)	(3.17)

Panel B: downgrades

	The post-recommendation cumulative abnormal returns (CARs)								
	2 days	30 days	60 days	90 days	120 days	150 days	180 days	270 days	360 days
Affiliated	-0.0230	-0.0154	-0.0434	-0.0438	-0.0336	-0.0126	0.0066	-0.0001	0.0359
	(-19.79)	(-3.12)	(-5.92)	(-5.08)	(-3.93)	(-1.27)	(0.65)	(-0.01)	(2.57)
Non-affiliated	-0.0132	0.0011	-0.0054	0.0016	0.0004	-0.0051	-0.0182	-0.0039	-0.0008
	(-17.87)	(0.37)	(-1.57)	(0.34)	(0.09)	(-0.99)	(-3.34)	(-0.58)	(-0.10)
Affiliated - Non-affiliated	-0.0098***	-0.0165***	-0.038***	-0.0454***	-0.0341***	-0.0075	0.025**	0.004	0.037**
	(-6.76)	(-2.89)	(-5.14)	(-4.82)	(-3.41)	(-0.71)	(2.22)	(0.27)	(2.25)

Table 2.8: Additional tests of CARs with conditioning variables

This table presents the additional tests for the short-term cumulative abnormal returns of affiliated and non-affiliated portfolios. I include only hedge fund tradings that are in the same direction as recommendation changes. The sample mean, t-statistics (in parenthesis), and mean difference are presented for the affiliated and non-affiliated portfolios. Star refers to the analyst that is ranked as an All-American in the annual polls in the Institutional Investor magazine. Influential refers to the influential recommendation change if its associated abnormal return is in the same direction as the recommendation change and is statistically significant (See Loh and Stulz (2011)). Panel A presents the results for recommendation changes made by star and non-star analysts. Panel B presents the results for influential and non-influential recommendation changes. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: star vs non-star

	The average post-recommendation cumulative abnormal returns (CARs)							
	Upgrades				Downgrades			
	2 days	30 days	60 days	90 days	2 days	30 days	60 days	90 days
Star								
Affiliated	0.0205	-0.0025	0.0735	0.0463	-0.0333	-0.0351	-0.1822	-0.1299
	(10.91)	(-0.12)	(4.38)	(1.64)	(-11.88)	(-2.80)	(-9.15)	(-4.92)
Non-affiliated	-	-	-	-	-0.0073	-0.0397	-0.0843	-0.2424
					(-6.21)	(-1.92)	(-3.29)	(-3.14)
Affiliated - Non-affiliated	-	-	-	-	-0.026***	0.005	-0.0979***	0.113*
					(-5.57)	(0.19)	(-2.70)	(1.76)
Non-star								
Affiliated	0.0206	0.0096	0.0094	0.0366	-0.0212	-0.0119	-0.0186	-0.0284
	(13.46)	(2.38)	(1.34)	(3.97)	(-16.93)	(-2.22)	(-2.64)	(-3.24)
Non-affiliated	0.0146	0.0058	-0.0163	-0.0250	-0.0133	0.0018	-0.0039	0.0061
	(17.59)	(1.27)	(-2.86)	(-3.43)	(-17.71)	(-0.64)	(-1.13)	(1.42)
Affiliated - Non-affiliated	0.006***	0.004	0.0260**	0.0620***	-0.0079***	-0.0138**	-0.0147*	-0.0346***
	(3.52)	(0.46)	(2.39)	(4.45)	(-5.04)	(-2.26)	(-1.93)	(-3.68)

Table 8 - continued

Panel B: influential vs non-influential

	The average post-recommendation cumulative abnormal returns (CARs)							
	Upgrades				Downgrades			
	2 days	30 days	60 days	90 days	2 days	30 days	60 days	90 days
Influential								
Affiliated	0.0437	0.0275	0.0100	0.0909	-0.0442	-0.0160	-0.0436	-0.0204
	(17.25)	(3.64)	(2.27)	(7.21)	(-31.60)	(-1.54)	(-3.57)	(-2.05)
Non-affiliated	0.0420	0.0417	0.0341	0.0788	-0.0403	-0.0381	-0.0045	-0.0070
	(49.34)	(5.27)	(2.97)	(4.16)	(-28.26)	(-6.02)	(-0.61)	(-0.72)
Affiliated - Non-affiliated	0.0020	-0.0142	-0.0242	0.0120	-0.004*	0.022*	-0.039***	-0.0134
	(0.83)	(-1.02)	(-1.25)	(0.37)	(-1.80)	(1.92)	(-2.92)	(-0.87)
Non-influential								
Affiliated	0.0206	0.0096	0.0094	0.0366	-0.0212	-0.0119	-0.0186	-0.0284
	(13.46)	(2.38)	(1.34)	(3.97)	(-16.93)	(-2.22)	(-2.64)	(-3.24)
Non-affiliated	0.0146	0.0058	-0.0163	-0.0250	-0.0133	0.0018	-0.0039	0.0061
	(17.59)	(1.27)	(-2.86)	(-3.43)	(-17.71)	(-0.64)	(-1.13)	(1.42)
Affiliated - Non-affiliated	0.006***	0.004	0.0260**	0.0620***	-0.0079***	-0.0138**	-0.0147*	-0.0346***
	(3.52)	(0.46)	(2.39)	(4.45)	(-5.04)	(-2.26)	(-1.93)	(-3.68)

Table 2.9: Hedge fund managers' skills and the post-recommendation cumulative abnormal returns

This table presents the tests for short-term cumulative abnormal returns of stocks invested by hedge funds with high and low alphas. Hedge funds are sorted into three terciles based on fund's alpha in a quarter, with the top and bottom terciles defined as high alpha and low alpha hedge funds, respectively. The sample mean, t-statistics (in parenthesis), and mean difference are presented for the affiliated and non-affiliated portfolios. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	The average post-recommendation cumulative abnormal returns (CARs)							
	Upgrades				Downgrades			
	2 days	30 days	60 days	90 days	2 days	30 days	60 days	90 days
High alpha								
Affiliated	0.024	0.009	0.025	0.037	-0.020	-0.028	-0.046	-0.039
	(7.56)	(0.92)	(2.01)	(2.39)	(-3.36)	(-2.40)	(-3.46)	(-2.44)
Non-affiliated	0.016	0.010	0.000	-0.015	-0.014	-0.003	-0.011	-0.010
	(6.76)	(1.21)	(0.00)	(-1.27)	(-6.13)	(-0.79)	(-1.85)	(-1.24)
Affiliated - Non-affiliated	0.008**	-0.0008	0.025**	0.053***	-0.006***	-0.024**	-0.036***	-0.029**
	(2.48)	(-0.06)	(2.27)	(2.66)	(-3.42)	(-2.30)	(-2.78)	(-2.10)
Low alpha								
Affiliated	0.021	-0.008	0.0005	0.010	-0.028	-0.016	-0.015	-0.020
	(8.85)	(-1.03)	(0.05)	(0.69)	(-6.61)	(-1.20)	(-1.15)	(-1.20)
Non-affiliated	0.015	0.006	-0.005	-0.010	-0.013	-0.007	-0.020	-0.014
	(6.07)	(0.79)	(-0.50)	(-0.73)	(-6.17)	(-1.42)	(-3.23)	(-1.59)
Affiliated - Non-affiliated	0.006**	-0.015	0.006	0.020	-0.015***	-0.008	0.005	-0.006
	(2.42)	(-1.02)	(0.40)	(1.22)	(-3.36)	(-0.73)	(0.36)	(-0.35)
High alpha - Low alpha								
Affiliated	0.003	0.017**	0.025**	0.027	0.008	-0.012	-0.031**	-0.018
	(0.77)	(2.50)	(2.31)	(1.28)	(1.11)	(-0.66)	(-2.00)	(-0.80)
Non-affiliated	0.002	0.003	0.006	-0.005	-0.0009	0.004	0.009	0.004
	(0.48)	(0.26)	(0.38)	(-0.28)	(-0.28)	(0.53)	(1.07)	(0.31)

Table 2.10: The exposure of recommendation factors to the movements in hedge fund returns

This table presents the exposure of hedge fund returns to analysts' recommendation changes. I construct recommendation factors by choosing 3 stocks with the highest earned profits out of those invested by affiliated hedge funds and 3 stocks with the highest earned profits out of those invested by non-affiliated hedge funds. I put each stock into one of the six barrels that belong to two different groups and rank the stocks by earned profits from high ($k = 1$) to low ($k = 3$) in each group. I refer to the time-series stock returns in each barrel as a recommendation factor. I regress the monthly hedge fund returns on the recommendation factors and the Fama-French-Carhart four factors.

$$R_{it} = \sum_{k=1}^{3} \beta_{ik}\ A.\ RecFactor_{kt} + \sum_{k=1}^{3} \gamma_{ik}\ NA.\ RecFactor_{kt} + \delta_1 MKT_t + \delta_2 SMB_t + \delta_3 HML_t + \delta_4 MOM_t + \epsilon_{it}$$

where $A.\ RecFactor_{kt}$ is the recommendation factor k in the affiliated group in month t, $NA.\ RecFactor_{kt}$ is the recommendation factor k in the non-affiliated group in month t, R_{it} is the return of hedge fund i in month t, and MKT_t, SMB_t, HML_t, and MOM_t are the Fama-French-Carhart four factors, respectively. β_{ik} and γ_{ik} are factor loadings on recommendation factor k in the affiliated and non-affiliated groups, respectively, which reflect the extent to which hedge fund returns are exposed to the recommendation changes. The last column tests the significance of the differences in the means, with p-values in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		Large hedge funds		Small hedge funds		Mean difference / t-value		
		β_{ik}	γ_{ik}	β_{ik}	γ_{ik}			
		(1)	(2)	(3)	(4)	(1)-(2)	(3)-(4)	(1)-(3)
k=1								
	Mean	0.515	0.230	0.258	0.171	0.285***	0.087***	0.257***
	Median	0.127	0.053	0.096	0.049	(7.28)	(3.09)	(4.59)
	Std dev	1.279	0.612	0.742	0.943			
	min	0.000	0.000	0.176	0.169			
	max	13.130	7.942	15.197	21.096			
k=2								
	Mean	1.216	0.588	0.641	0.274	0.628***	0.366***	0.575***
	Median	0.231	0.124	0.248	0.087	(5.67)	(6.75)	(3.76)
	Std dev	3.645	1.352	1.735	0.697			
	min	0.001	0.0005	0.000	0.000			
	max	27.291	11.563	25.116	12.368			
k=3								
	Mean	1.425	0.797	0.750	0.481	0.629***	0.269***	0.675***
	Median	0.441	0.187	0.404	0.139	(6.07)	(4.92)	(4.34)
	Std dev	3.640	2.276	1.899	1.095			
	min	0.0005	0.0001	0.0007	0.0005			
	max	46.263	22.647	41.315	1.808			

CHAPTER 3

HOLDINGS CONCENTRATION AND HEDGE FUND INVESTMENT STRATEGIES

3.1 Introduction

Hedge funds are documented to play an important role in equity market and dominate trading of certain stocks (Stein, 2009). It is generally agreed that markets are more efficient when it comes to pricing large-cap stocks and less efficient for small-cap stocks. In this context, studying the consensus wisdom in stock holding under different market efficiency can help us understand fund managers' skills in exploiting information advantages.

In this paper, we examine the investment value and risk consequence of stock holdings concentration displayed by hedge funds. Hedge funds might focus their equity investments on certain stocks if they believe the stocks will outperform the market or if they have superior information about the profitability of the stocks. To assess the information content in funds investment, we investigate the active holdings of hedge funds and aggregate their decisions on the stock level. If active hedge funds deviate from benchmarks in a way that reveals information scattered among managers, the aggregate measure can be used to capture information advantages and predict future performance of stocks.

As one of the most sophisticated traders, hedge funds exhibit skills not only in popular picks, but more importantly, they spend enormous resources on researching companies overlooked by others. It is reported that 80% of Wall Street research is focused on 20% publicly traded companies with market capitalization of over $1.5 billion, leaving a large number of small companies with scant analyst coverage. For small companies, there is a greater possibility of market inefficiencies due to a liquidity problem caused by relatively few freely traded shares. However, small companies have higher growth and are more likely to increase shareholder value over time. Analyzing and uncovering data about small companies will increase the chance of generating significant outcomes.

The first goal of this study is to examine whether hedge funds are skilled in equity investments under different market efficiency. Specifically, we measure and test the future performance of large-cap and small-cap stocks sorted by the holdings concentration of hedge funds. For each stock, holdings concentration is measured by aggregating the deviations of funds' holdings from benchmarks. To maximize benchmark-adjusted return, an active manager would overweight a stock if he believes the stock will outperform and underweight it otherwise. As a result, stocks with higher holdings concentration are expected to have higher future returns, especially in an inefficient market.

Despite the expected future performance, hedge fund holdings concentration may be associated with substantial downside risks. Stein (2009) points out that hedge funds are forced to delever as a result of negative return shocks in a security, and the crowding of levered funds could drive the prices of the securities further down and lead to a fire sale effect. Different than fund crowds, holdings concentration evaluates the extent to which a fund focuses on a stock rather than the number of funds holding a stock. Previous research documents that hedge fund crowding was a key contributor to the financial crisis over the past 20 years (e.g. Kyle and Xiong (2001), Khandani and Lo (2011), and Acharya, Philippon, Richardson, and Roubini (2009)). However, there is no direct examination of the downside risks associated with holdings concentration.

Therefore, the second goal of this study is to examine whether holdings concentration impose additional risks, especially when hedge funds are forced to delever during financial crisis? Specifically, we test whether (i) stocks with higher holdings concentration have higher downside risk, (ii) holdings concentration contributes to the low stock performance during financial crisis, and (iii) hedge fund leverage exacerbates the negative impact of holdings concentration?

Using a comprehensive dataset of hedge funds and SEC 13F fillings, we find that stocks, either large-cap or small-cap, heavily overweighed by active hedge funds, relative to their benchmark index, perform substantially better than those being underweighted. The average return spread of equal-weight stock portfolios is 1.34% for small-cap stocks and 0.63% for large-caps, after adjustments for loadings on market, size, value, and momentum factors. The spread is 0.65% for small-caps on a value-weight basis, whereas it is insignificant for value-weight large-cap portfolios. These results demonstrate the superior ability of hedge fund manager to trade stocks in both efficient and inefficient markets. As managers are required to have better skills to process information in an inefficient market, the portfolio tilting decisions by hedge funds are more valuable in trading small-cap stocks.

The results in this study establish a strong relation between holdings concentration and stock future performance. Our findings show that both large-cap and small-cap stocks with concentrated hedge fund holdings earn higher future returns than those with lower holdings concentration. The results demonstrate that there is no return reversal for stocks that hedge funds concentrate on, and the funds' deviation from benchmarks positively predicts firms' future performance. Consistent with Grossman and Stiglitz (1980) and Cao, Liang, Lo, and Petrasek (2014), our findings suggest that hedge funds possess value-relevant information that is not fully incorporated into stock prices, and the aggregate deviation from benchmarks can help impound information into stock prices.

We find the evidence that the holding period stock returns up to one year subsequent to the identified holdings concentration are persistently positive. we design a long-short strategy that buys the stocks that average funds overweight and shorts the stocks that they underweight and test the equal-weight portfolio abnormal returns in the following quarters. The strategy generates an equal-weight alpha of 0.88% for large-cap portfolio and 0.86% for small-cap portfolio in the first quarter and then starts experiencing negative abnormal returns in the subsequent quarters, especially for small-cap stocks. For example, the long-short strategy deployed on small-cap stocks with a delay of a quarter earns 2.39% less abnormal return generated by the same strategy implemented without a lag. These results suggest that the investment value of concentrated portfolio dissipates quickly after fund holdings become publicly available, as the Securities and Exchange Commission (SEC) requires hedge funds to disclose their portfolio with a maximum delay of 45 days. Our results also suggest that it is possible to earn positive abnormal returns by replicating hedge fund equity investment strategies based on SEC 13F fillings[1].

By examining stock portfolios sorted by holdings concentration, we find that both large-cap and small-cap stocks with concentrated hedge fund holdings have higher standard deviation and downside risks. The results are statistically significant at 1% level based on both traditional and Newey-West (1987) t-tests. These results suggest that holdings concentration could contribute to the risk that a stock faces. As informed trading by fund managers can play an important role in determining stock prices, concentrating on a stock could drive prices from fundamentals and increase the risks associated with it. Moreover, the returns of small-cap stocks tend to skew to the right, and at each level of holdings concentration, risks associated with small-cap stocks are relatively higher than those for large-cap stocks. These findings suggest that, although small-cap stocks are less efficiently priced, managers are capable of earning abnormal returns after controlling for risk factors.

We further examine whether the differential effect of holdings concentration is related to hedge funds' use of leverage. According to Stein (2009) and Brunnermeier and Pedersen (2009), hedge fund leverage exacerbates negative externalities of hedge fund crowds and create a fire sale during financial crisis. Consistent with previous studies that deleverage leads to the negative return shock and downside risk in stocks, we find that small-cap stocks are concentrated by hedge funds using relatively high leverage. Meanwhile, levered hedge

[1]For example, the AlphaClone Inc. deploys an investment strategy through analyzing SEC public filings to learn the profitable positions held by sophisticated investors, and then building an index based on the observed confident holdings.

funds are less likely to concentrate their holdings on large-cap stocks, in order to avoid big losses in the potential market downturns.

This study contributes to the literature on active portfolio management. It illustrates the need to understand the relationship between active holdings and manager skills in balancing risks and returns. Recent studies support the notion that active holdings predict future performance. Cremers and Petajisto (2009) introduce active share to quantify active portfolio management and find that active management predicts fund performance. Kacperczyk, Sialm, and Zheng (2005) show that mutual funds with higher industry concentration achieve better performance. Jiang and Sun (2014) find a strong link between the dispersion in beliefs among active mutual funds and future stock returns. Using an aggregate stock-level measure, this study supports the notion that active holdings predict individual stock future performance. The test results imply that fund managers are skilled at exploiting information advantages under different market efficiency.

This study also adds to the growing literature on hedge funds' impacts on equity market. Previous studies, such as Billio, Getmansky, Lo, and Pelizzon (2012) and Boyson, Stahel, and Stulz (2011) document that hedge funds play an important role in spreading financial crisis. Brunnermeier and Nagel (2004) and and Griffin, Harris, Shu, and Topaloglu (2011) find that hedge funds overweight high-priced technology stocks from 1998 to 2000 and sold off those stocks quickly when the bubble start to burst. Cao, Liang, Lo, and Petrasek (2014) show that increased hedge fund ownership leads to improved informational efficiency of stock prices. This study adds to the literature by examining the downside risks associated with aggregated active holdings. Our results provide evidence that levered hedge funds contribute to the high risk and low performance during financial crisis.

We organize the rest of this paper as follows. Section 3.2 introduces the measuring variables and presents sample construction and summary statistics; Section 3.3 explore the information content of holdings concentration by examining stock future returns; Section 3.4

presents risk analyses for stock with different levels of holdings concentration; Section 3.5 concludes the paper.

3.2 Measuring variables and sample construction

In this section, we introduce the construction of measuring variables, followed by sample construction and summary statistics for hedge funds and stocks.

3.2.1 Measurements for holdings concentration

To capture managers' consensus beliefs about the value of individual stocks, we construct a measuring variable based on the aggregation of funds' active holdings. The funds' active holdings for a given stock are defined as the difference between the weight of the stock in each fund manager's portfolio and that in the benchmark index[2]. Managers overweight a stock if they expect it to outperform the benchmark index and underweight it otherwise. An aggregate measure of managers' decisions to deviate from benchmark captures the consensus view of managers on the future value of stocks based on their information set.

We define holdings concentration as the aggregation of managers' active holdings. Our measure is based on Lakonishok, Shleifer, and Vishny (1992). Specifically, we use an stock level measure by averaging the holdings deviation from benchmarks across all hedge funds holding the stock. Letting HC measures the concentrated holdings of hedge funds that deviate above (or below) the benchmark index of stock i during quarter t.

$$HC_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} [(w_{i,t}^{j} - w_{i,t}^{b}) - E(w_{i,t}^{j} - w_{i,t}^{b})] \tag{3.1}$$

Where $w_{i,t}^{j}$ is the weight of stock i in fund j's portfolio at the end of quarter t, $w_{i,t}^{b}$ is the weight of stock i in the benchmark portfolio at the end of quarter t, and $N_{i,t}$ is the number of funds invested in stock i at quarter t. $E(w_{i,t}^{j} - w_{i,t}^{b})$ is an adjustment factor to allow

[2]See Cremers and Petajisto (2009).

for random variation around expected deviation under the null hypothesis of independent trading decisions by the funds. We average the difference in portfolio weights across all stocks held by hedge fund j as a proxy for $E(w_{i,t}^j - w_{i,t}^b)$.

This equation defines and measures holdings concentration as the tendency of hedge funds to weigh a given stock together and in the same direction more heavily than would be expected by funds trading randomly and independently. Except for the overall funds, we can measure the extent to which any subgroup of funds deviate from benchmarks by calculating HC for that group. Stock with higher HC are anticipated to have a higher holdings concentration.

We also use a conditional HC to measure concentrated holdings separately for hedge funds overweight and underweight the stocks. We call the concentrated holdings deviation as OHC for overweighted holdings and as UHC for underweighted holdings.

$$OHC_{i,t} = HC_{i,t} | w_{i,t}^j > w_{i,t}^b \tag{3.2}$$

$$UHC_{i,t} = HC_{i,t} | w_{i,t}^j < w_{i,t}^b \tag{3.3}$$

We average HC separately for these two measures based on how many fund holdings are overweighted and underweighted. Thus, these measures are useful in analyzing stock future performance following concentrated trading activities.

3.2.2 Sample and summary statistics

We use TASS database to identify all the hedge funds and hedge fund management companies. The TASS database is one of the most comprehensive hedge fund database consisting of monthly hedge fund returns, asset under management (thereafter, AUM), leverage, and other fund-specific information. We used both Live" and Graveyard" funds to mitigate a potential survivorship bias.

We identify hedge fund equity holdings based on institutional holdings from 13F fillings to Securities and Exchange Commission (SEC). As a private investment company, hedge funds with more than \$100 million under management must report their holdings to the SEC each quarter on form 13F, including all long positions (but no short position) in U.S. stocks and a few other securities greater than 10,000 shares or \$200,000 in the market value. Holdings are reported at the management company level at the end of each calendar quarter.

Following the methodology of Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we compile a list hedge fund management companies from TASS hedge fund databases, and manually match them with the companies registered as investment advisers from 13F database. If a firm is not registered, We include it in the sample, since registration is a prerequisite for conducting non-hedge fund business such as advising mutual funds and pension plans. If the firm is registered, we obtain its ADV form and check its eligibility for the sample based on two criteria: (1) at least 50% of its clients are Other pooled investment vehicles (e.g., hedge funds)" or High net worth individuals," and (2) it charges a performance fee for its advisory services. This process leaves us with 380 companies and 25,633 total stock holdings.

Since holdings data are company-based, we upgrade fund-level characteristics in TASS to the company-level to satisfy the consistency requirements. For example, a hedge fund company's asset under management is calculated as the sum of AUMs of all hedge funds managed by the company at each time point. We include only hedge funds that have at least \$1 billion asset under management and have no less than 6 quarters of observations.

To construct our data set, we combine the Center for Research in Security Prices (CRSP) with TASS and 13F fillings. CRSP provides monthly returns, prices, and market values of equity for common stocks traded on the NYSE, AMEX, and NASDAQ. We exclude closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, and primes. We eliminate stocks with prices below \$5 at the portfolio formation date. We divide stocks in our sample into large-cap and small-cap stocks by mapping stocks to S&P500 index and Russell 2000 index, respectively. The S&P500 index and Russell 2000 index are from Bloomberg.

Table 3.1 Panel A and Panel B report the summary statistics for our hedge fund stock holdings sample, which include a universe of 280 hedge fund management companies with 723 large-cap stocks and 3,856 small-cap stocks, spanning the period from 1994 to 2014. On average, there are 167 large-cap stocks and 408 small-cap stocks held by each hedge fund. A hedge fund invests \$2.241 billion in large-cap stocks and \$0.268 billion in small-cap stocks on average. These results suggest that hedge fund managers not only invest in large-cap stocks as other regular investors but also find ways to make money from small-cap stocks. The overweighted holdings concentration is relatively bigger in large-cap stocks than that in small-cap stocks, whereas underweighted holdings concentration is comparable across two types of stocks. Panel C presents quintile ranked statistics based on holdings concentration for large-cap and small-cap stocks. Holdings concentration for small-cap stocks spans wider from -0.821 to 0.837 than large-cap stocks from -0.283 to 0.513. The number of funds holding a large-cap stock decrease as holdings concentration increase, whereas the number of funds holdings a small-cap stock increase as holdings concentration increase.

Table 3.2 reports the summary statistics of the characteristics of hedge funds invested in stock portfolios ranked by holdings concentration. Panel A and Panel B show the results for hedge funds holding large-cap and small-caps stocks, respectively. The hedge fund characteristics include AUM_t (in millions), which is calculated as the sum of AUMs of all the hedge funds managed by a fund company at quarter t; $Big\ HFs$, which is calculated as the number of hedge funds with AUM greater than \$10 billion in each fund company; $Return_{t-1}$, which is calculated as the percentage change of the net asset values of the fund company between the beginning and the end of quarter $t-1$; $Return\ Std_{t-1}$, which is calculated as the standard deviation of the return of a hedge fund company in quarter $t-1$; Age_t (in months), which is calculated as the asset weighted average age of the managed hedge funds. The summary statistics suggest that smaller hedge funds with higher past returns are more likely to concentrate their holdings on either large-cap or small-cap stocks.

3.3 Holdings concentration and stock future performance

In this section, we evaluate the investment value of stock holdings concentrated by hedge funds. We begin the analysis by examining the relationship between holdings concentration and future stock returns. Then we evaluate the information content of the aggregate active holdings and its implications for stock market efficiency and potential investment strategies.

3.3.1 Subsequent stock returns

According to Grossman and Stiglitz (1980), investors who are skilled at acquiring information through more efficient collection or processing of available information will be rewarded with higher returns. Therefore, investigating the investment value of aggregate active holdings can help us discover the information content of aggregate active holdings of hedge fund and evaluate managers' skills.

To understand how holdings concentration is related to the subsequent stock returns, at the end of each quarter we sort stocks into quintiles in ascending order based on hedge fund holdings concentration. The holdings concentration is computed using HC, OHC, and UHC measures, separately. We then compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter. To adjust for risk, we consider various factor models, including the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model. We also use the characteristic-based benchmarks proposed by Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) to account for the possible nonlinear relation between characteristics and returns. We perform the analysis for large-cap stocks and small-cap stocks separately.

Panel A of Table 3.3 presents the results for the equal-weight and value-weight large-cap stock portfolios using HC as measuring variable. We find that average portfolio returns increase with concentration in active fund holdings in the past quarter. For stocks in the top quintile with the highest holdings concentration, the average return is 1.66% per month, whereas the average return for stocks in the bottom quintile with the lowest holdings concentration is only 0.78% per month. The return spread of 0.88% per month is statistically significant with a t-statistic of 10.33. To test whether the significantly positive return spread can be explained by managers' propensity to take risks, we examine the abnormal returns using four risk-adjusted models. For example, from Carhart four-factor model, stocks in the top quintile with highest holdings concentration realize an average abnormal return of 0.49%, whereas stocks in the bottom quitile with lowest concentration earn an average abnormal return of 0.01%. A long-short strategy that buys stocks in the top quitile and short stocks in the bottom quintile generates an average monthly abnormal return of 0.48% in the subsequent quarter with t-statistic 5.57.

The value-weight large-cap portfolio presents similar increasing relationship between holdings concentration and the subsequent stock returns. Moreover, the difference in raw returns between portfolios with high concentration and low concentration remains statistically significant and economically large. However, after controlling for risks, the some return spreads become insignificant. For example, from the Fama-French three-factor model and Carhart four-factor model, the average abnormal returns do not show monotonic increasing relationship with holdings concentration. Their differences in abnormal returns between portfolios with high and low holdings concentration are not significant. According to Fama and French (2008), value-weight portfolio returns may be driven by a few very large-cap stocks. As very large cap stocks are efficiently priced, hedge funds own little information that has not been incorporated into their price. Therefore, the concentrated holdings in vary large cap stocks presents little investment value for hedge funds.

Panel B of Table 3.3 presents the results for small-cap stock portfolios using HC as measuring variable. We find similar positive relationship between holdings concentration and average equal-weight portfolio returns for small-cap stocks. For stocks in the top quitile with the highest holdings concentration, the average return is 1.78% per month, whereas the average return for stocks in the bottom quitile with the lowest holdings concentration is 1.30% per month. The return spread of 0.48% per month is statistically significant with a t-statistic of 6.50. The results hold when we examine the abnormal returns using four different risk-adjusted models. The difference in Carhart four-factor abnormal returns between portfolios with high and low concentrations is 1.34%, which is statistically significant and economically large. In addition to the equal-weight portfolios, value-weight portfolios present similar spreads in both average raw return and average abnormal returns calculated using four different risk-factor models.

Panel C and Panel D show the average monthly returns for stock portfolios using overweighted holdings concentration (OHC) and underweighted holdings concentration (UHC), respectively. For both large-cap and small-cap stocks in the top quintile with the highest OHC, the average raw returns and abnormal returns are significantly higher than those in the bottom quitile with the lowest OHC. In contrast, for stocks in the top quintile with the highest UHC, the average raw returns and abnormal returns are significantly lower than those in the bottom quitile with the lowest UHC. These results provide evidence that hedge funds overweigh stocks with high investment value and underweigh stocks with low investment value.

From the above tests, compared to large-cap stocks, small-cap stocks display higher investment value in the concentrated hedge fund holdings, as both their average raw returns and abnormal returns are higher than those of large-cap stocks. Moreover, as evaluated by four different risk-adjusted models, the abnormal return spreads of small-cap portfolio are also higher than those of large-cap stock portfolios.

In summary, we find that the stock-level aggregate holdings concentration of active hedge funds positively forecast future stock returns. Our results provide evidence that deviation from benchmarks reflects managers' information on stock future performance. We also find that the investment values of concentrated holdings are significantly positive, especially in small-cap stocks. Our results suggest that fund managers have skills to collect and process information in an inefficient market, and the information is more valuable than that in an efficient market.

3.3.2 Holding period returns

To evaluate the performance of concentrated stock portfolios with different holding period, we compare the cumulative abnormal returns of concentrated and non-concentrated portfolios. Concentrated and non-concentrated portfolios refer to stock portfolios with the highest and lowest holdings concentration, respectively. At the end of each quarter t, we sort stocks into quintiles in ascending order based on hedge fund holdings concentration (HC). Then start from time t, we compute the cumulative DGTW-adjusted abnormal returns over the subsequent 1, 2, 3, 6, 9, and 12 months.

Panel A of Table 3.4 presents the average cumulative abnormal returns of concentrated and non-concentrate stock portfolios. We find that, for both large-cap and small-cap stocks, the average portfolio alpha increases with increasing number of months. For large-cap stocks, the average alphas of concentrated portfolio over the subsequent time periods are higher than those of non-concentrated portfolios. These results are all statistically significant and economically large.

In contrast, for small-cap stocks, the average alpha of concentrated portfolios is significantly higher than that of non-concentrated portfolios only within one-month $(t, t+1)$, two-month $(t+1, t+2)$, and three-month $(t+1, t+3)$. For example, the first quarter average alpha is 2.17% for the concentrated portfolio and 0.88% for the non-concentrated portfolio. The difference of average alpha between these two portfolios is 1.29% with t-statistic 9.08. For cumulative time period greater than a quarter, the average alpha of the non-concentrated portfolio increases with increasing number of months in a larger magnitude than that of the concentrated portfolio. The average alpha spreads are significantly negative within three-quarter $(t+1, t+9)$ and four-quarter $(t+1, t+12)$ time periods.

Our results provide evidence that hedge funds can earn significantly positive abnormal returns by applying long-short strategy on the concentrated and non-concentrated stocks with different holding periods. Consistent with the note that small-cap stocks are less efficiently priced, our results suggest that short-term trading on small-cap stocks can generate significant amount of profits for hedge funds.

3.3.3 Market efficiency

If hedge funds have informational advantages about the stocks they overweight, we expect that the value-relevant information will be incorporated into stock prices and reflected on the stock returns. In this subsection, we study how fast the information is incorporated into stock prices and what are the implications of holdings concentration for market efficiency.

We deploy a long-short strategy that buy stocks that hedge funds overweight in the concentrated portfolios and short stocks that they underweight in the non-concentrated portfolios. We compute the equal-weight DGTW alpha on these strategies in the following three months ($M1$, $M2$, and $M3$) and four quarters ($Q1$, $Q2$, $Q3$, and $Q4$). We also use DGTW alpha $Alpha_0$ on the strategy in the current month (quarter) as a benchmark to measure the information content of holdings concentration. The monthly (quarterly) alphas as well as alphas deflated by the benchmark alpha reflect the speed that information is incorporated into stock prices and lead to zero abnormal return.

Panel B of Table 3.4 presents our test results for market efficiency. For both large-cap and small-cap stocks, alphas in the first two months are positive and significant and become negative in the third month. For example, the alpha for small-cap stocks is 0.71% with t-statistic 17.56 in the first month and 0.28% with t-statistic 6.97 in the second month, and then it becomes -0.21% with t-statistic -5.56 in the third month. Similar pattern can be found in quarterly alpha of large-cap and small-cap stocks. The first quarter alpha is significantly positive and then become negative in the following quarters. We also find that the deflated alphas are significantly negative for large-cap and small-cap stocks and decrease over all the subsequent time units.

Our results show that there is a time trend of enhanced market efficiency, and at some point between the second and third month, abnormal return approaches zero. We find that the speed that information is incorporated into stock prices is comparable across large-cap and small-cap stocks. However, there seem to be relatively larger amount of information contained in the small-cap stocks concentrated by hedge funds than that contained in large-cap ones. In addition, as the SEC requires all hedge funds to disclose their portfolio holdings with a maximum delay of 45 days, it is possible to earn positive abnormal returns by replicating hedge fund equity investment strategies based on SEC 13F fillings.

3.4 Holdings concentration and risk analysis

In this section, we perform the risk analyses on stocks with different levels of holdings concentration. Then we examine the relationship between hedge fund leverage and the concentration of their stock holdings.

3.4.1 Downside risks

So far we have shown the investment value of stock with concentrated hedge fund holdings by examining the relationship between holdings concentration and future stock returns. A concern we address here is whether holdings concentration imposes additional risk on stocks, especially hedge funds are forced to delever during financial crisis. Stein (2009) points out that hedge funds are forced to delever as a result of negative return shocks in a security, and the crowding of levered funds could drive the prices of the securities further down and lead to a fire sale effect. A stock's potential to suffer a decline in value during financial crisis can be captured by measuring downside risks of stocks in various ways. In this section, we compare the downside risks of stock portfolios sorted by hedge fund holdings concentration. We expect to see higher downside risk associated with stocks with higher holdings concentration if the aggregate holdings deviation from benchmark destabilizes the market.

To properly value the risks associated with stocks, we deploy several measures. First, we compute the standard deviation, skewness, and kurtosis of stock returns according to Liang and Park (2007). At the end of each month starting from January 1999, we use 60 months rolling windows of previous returns to estimate the standard deviation and other risk measures of each stock. That is, our five-year estimation window starts in January 1994, and the test period spans 120 months from January 1999 to December 2014. If the stock is available after January 2009, we use whatever return history is available during this time period as long as the window is at least 24 months. For consistency, the same rule is applied for other measures that we will introduce in the following.

Second, we use Value-at-Risk (VaR), Expected Shortfall (ES), and Tail Risk (TR) as measures of downside risks. Although traditional risk measures we introduced above are still dominant among practitioners, they may not capture many of the risk exposures of stocks concentrated by hedge funds. According to the arbitrageur leverage model in Stein (2009), hedge fund leverage exacerbates the negative externalities of hedge fund crowds due to contagion effects during financial crisis. Therefore, the use of leverage and return structure of hedge funds make it necessary to examine downside risks of the stocks concentrated by hedge funds.

Value-at-Risk (VaR) is the maximum loss that can happen over a specific time horizon at a specified confidence level. To estimate VaR, we choose the confidence level $(1-\alpha)$, the time horizon (τ), and the estimation model. The statement we can make based on the estimation model is: we are $(1-\alpha)$ percent certain that we will not lose more than $VaR(\alpha,\tau)$ dollars in τ days. In this study, we use the Cornish-Fisher (1937) expansion to estimate VaR in the following, as the return distribution are skewed and leptokurtic and it is inappropriate to use traditional VaR.

$$VaR(\alpha) = -(\mu + \Omega(\alpha) * \sigma) \tag{3.4}$$

Where μ is the average return, σ is the standard deviation, $\Omega(\alpha)$ is the Cornish-Fisher expansion with skewness and kurtosis incorporated, and $1-\alpha$ is the confidence level.

Expected Shortfall (ES) makes up for a shortcoming of VaR and quantifies the average losses that are greater or equal to VaR. Based on the 95% Cornish-Fisher VaR calculated above, we estimate ES using the following formula.

$$ES_t(\alpha, \tau) = -E_t[R_{t+\tau} | R_{t+\tau} \leq -VaR_t(\alpha, \tau)] \tag{3.5}$$

Where $R_{t+\tau}$ is the stock return during the period between t and $t+\tau$ and $VaR_t(\alpha, \tau)$ is the Cornish-Fisher VaR at the $1-\alpha$ confidence level.

Tail Risk (TR) measures the deviation of losses greater or equal to VaR from mean. Relative to VaR and ES, TR can best capture the impact of an extremely low return observation as the deviations from mean are squared. TR is defined as follows.

$$TR_t(\alpha, \tau) = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau})^2 | R_{t+\tau} \leq -VaR_t(\alpha, \tau)]} \tag{3.6}$$

We execute the above mentioned 6 risk measures for all the stocks in our sample. To understand the relationship between holdings concentration and downside risks, we sort stocks into quintiles in ascending order based on holdings concentration (HC) at the end of each quarter. The time series average of the cross sectional risks of all stocks in each quintile is computed using our 6 different measures. We perform the analysis for large-cap and small-cap stocks separately. To deal with the autocorrelation problem that might arise from the 60-month overlapping window, we present the t-statistics based on the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix as well as the traditional t-statistics.

Panel A of Table 3.5 presents the risk analysis for large-cap stocks sorted by hedge fund holdings concentration. We find that the expected return and the average standard deviation of all the stocks in the portfolio are positively related to the holdings concentration. For stocks in the top quintile with the highest holdings concentration, the expected return and the standard deviation is 1.578% and 0.108, respectively, whereas they are 1.054% and 0.081 for stocks in the bottom quintile with the lowest holdings concentration. The spread of standard deviations between the highest and lowest holdings concentration is 0.027 with a standard t-statistic of 54.80 and a Newey-West t-statistic of 25.74.

We next find that the average skewness of stocks in the top quintile of holdings concentration is 0.063, whereas stocks in the lower quintiles are left-skewed on average. The spread of skewness between portfolios with the highest and lowest holdings concentration is positive and significant, however, the skewness does not increase monotonically with the holdings concentration. For example, the skewness is -0.009 in the second lowest quintile but -0.027 in the second highest quintile. Our results also show that the distribution stock returns in every quintile ranked from low to high are leptokurtic. Similarly, although the spread of kurtosis is significantly positive, the kurtosis does not increase monotomically with the holdings concentration.

We further find that the average VaR, ES, and TR increase monotonically with holdings concentration. For example, the average VaR, ES, and TR in the bottom quintile with the lowest holdings concentration are 0.118, 0.871%, and 0.041, respectively, whereas they are 0.152, 1.109%, and 0.052, respectively, in the top quintile with the highest holdings concentration. The spreads of VaR, ES, and TR between portfolios with the highest and lowest holdings concentration are all positive and significant.

Panel B of Table 3.5 reports the risk analysis for small-cap stocks sorted by holdings concentration. The risk measures of small-cap stocks present similar patterns as those of large-cap stocks. The average return, standard deviation, VaR, ES, and TR all increase monotonically with the increase of holdings concentration, with the risk values greater than those of large-cap stocks in the corresponding quintile. Stocks in every quintile are right-skewed and leptokurtic on average. The average skewness of stocks in the top quintile of holdings concentration is significantly higher than that of stocks in the bottom quintile, and both skewness and kurtosis do not increase monotonically with holdings concentration.

In summary, our results provide evidence that stocks, either large or small, with concentrated hedge fund holdings are associated with higher downside risks than those with less concentrated holdings. Small-cap stocks are relatively riskier than large-cap stocks, as small stocks are less efficiently priced and unstable during a rare event. Making an investment in small-cap stocks requires higher skills of fund managers.

3.4.2 Stock performance drop

Our tests above tell us that stocks with concentrated hedge fund holdings are associated with higher downside risks. In this subsection, we examine the impact of holdings concentration on stock performance in market downturns. Would the consensus deviations from benchmarks drive stock prices down more quickly and exacerbate financial crisis?

To examine the negative impact of holdings concentration, we focus on stocks with decreased quarterly Carhart abnormal returns. We calculate the expected change of stock returns ΔR_{t+1} ($\Delta R_{t+1} = R_{t+1} - R_t$) as the difference between the stock return at the end of quarter $t+1$ and the stock return at the end of quarter t. We present the quarterly changes of raw returns as well as risk adjusted returns of the concentrated and non-concentrated portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the portfolio performance using the DGTW (1997) characteristic adjustment. The decrease of stock returns ΔR_{t+1} subsequent to the identified holdings concentration reflects the negative impact of holdings concentration on the already low stock performance. We perform the analysis separately for crisis period, which includes year 2001 and 2007 Q4 - 2009 Q1, and for normal period.

Panel A of Table 3.6 presents the average quarterly change of large-cap stock returns for the concentrated and non-concentrated portfolios. We find that the abnormal returns of stocks with concentrated hedge fund holdings decrease more than those of stocks with non-concentrated holdings. For example, the average decrease of Carhart alphas are -4.95% for the concentrated portfolio and -2.29% for the non-concentrated portfolio during crisis period, and are -3.61% and -2.58% for the two portfolios, respectively, during normal period. The results are significantly negative in both crisis and normal periods.

Panel B of Table 3.6 presents the average quarterly change of small-cap stock performance. Similar to those of large-cap stocks, the abnormal returns of stocks with concentrated hedge fund holdings decrease more than those of stocks with non-concentrated holdings during crisis period. However, the decreases of Carhart alphas are comparable across two portfolios in normal period. In addition, the decreases of abnormal returns of the long-short strategy during crisis period are significantly negative and smaller than those during normal period. For example, the decrease of long-short DGTW alpha is -4.16% during crisis period, whereas it is -2.73% during normal period. Our results suggest the greater impacts of holdings concentration during crisis periods.

Our results provide evidence that concentrated holdings of hedge funds expedites the decrease of stock abnormal returns, especially during financial crisis. Our results suggest that holdings concentration has negative impacts on stock performance and could be a catalyst for financial crisis.

3.4.3 Hedge fund leverage

Previous studies document that hedge fund deleverage leads to the negative return shocks and downside risks in stocks. In this subsection, we examine whether the relatively high risks associated with stocks concentrated by hedge funds are related to the use of leverage by hedge funds. If the aggregate overweighting is a factor that deteriorate the negative impact of hedge fund deleverage, we expect to see a positive relationship between average leverage of hedge funds that holding a stock and the holdings concentration of the stock.

We use three measures to proxy for the hedge fund leverage. First, we compute the ratio of 13F equity holdings to hedge fund company's AUM. We remove samples with the 13F equity holdings/AUM ratio greater than 10%, which leaves us with about 90 percent of original samples. We expect that the 13F equity holdings/AUM ratio is negatively related to the use of leverage by hedge funds. Second, we calculate the number of big prime brokers that a hedge fund uses. Prime brokers typically offer services such as margin financing, security lending, etc. to hedge funds. Hedge funds that use higher leverage are more likely to get service from big prime brokers[3], as big prime brokers are capable of providing them with enough cash and a variety of securities to borrow. As a result, a positive relationship between the number of big prime brokers and hedge fund leverage is expected. Third, we use the average leverage of a hedge fund company as a direct proxy. The average leverage of a fund company is calculated as the mean value of the average leverage of all hedge funds managed by the company. The average leverage of a hedge fund is provided by TASS database.

Panel A and Panel B of Table 3.7 presents the relationship between hedge fund leverage and the holdings concentration in large-cap and small-cap stocks, respectively. We find that the results are as expected for small-cap stocks. That is, hedge fund leverage is positively related to the holdings concentration of small-cap stocks. Our results show that, as the holdings concentration increases, the 13F equity holdings/AUM ratio decreases and the number of big prime brokers and average leverage increase. The spreads of these three measuring variables between portfolios with the highest concentration and lowest concentration are -0.014, 0.956, and 0.276 with t-statistics -6.94, 3.66, and 2.43.

For large-cap stocks, however, the results are quite the opposite. The 13F equity holdings/AUM ratio increases with the holdings concentration, and the number of big prime brokers and average leverage decrease with the holdings concentration. The measuring spreads between concentrated and non-concentrated portfolios are all statistically significant.

Our results suggest that, consistent with the note that small-cap stocks are less efficiently priced, the concentration of leveraged hedge funds may easily impose additional risks on small

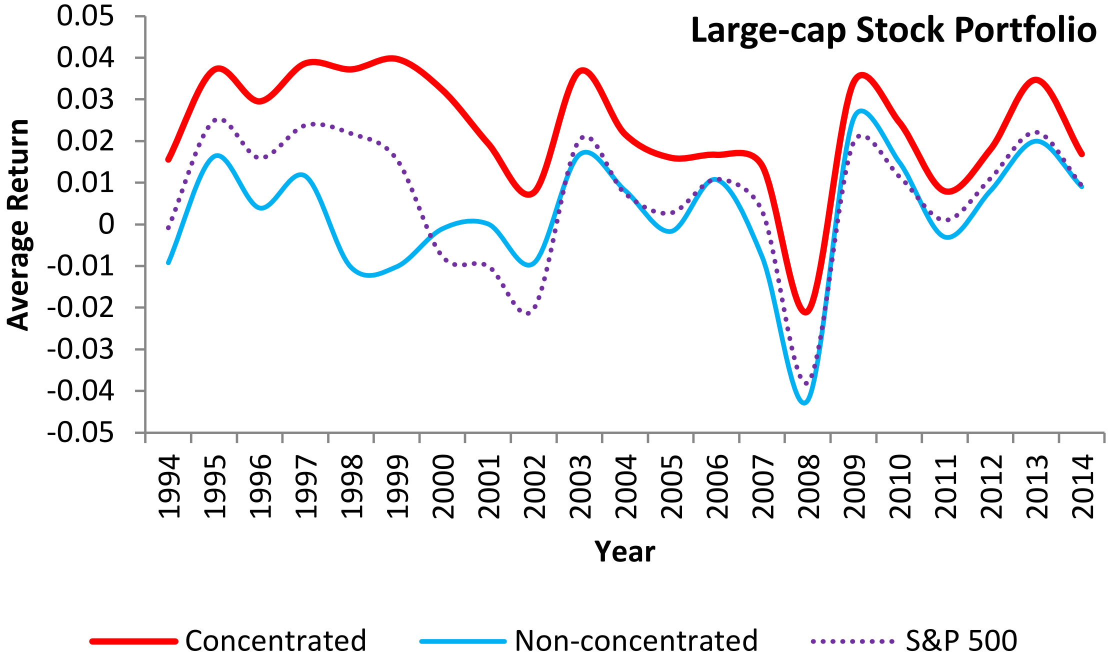
[3]According to the snapshots of TASS data from 2006 to 2012, the eleven major prime brokers ranked by their average market share were Goldman Sachs, JP Morgan, Morgan Stanley, Credit Suisse, Deutsche Bank, UBS, Citi, Lehman Brothers, Bear Stearns, Bank of America, and Merrill Lynch. In TASS, there are 465 global prime brokers, with top 11 biggest prime brokers account for about 86% of the market share in hedge fund businesses.

stocks. In addition, levered hedge funds may choose to diversify their holdings in large-cap stocks, in order to avoid big losses in the potential market downturns.

3.5 Conclusion

This paper studies hedge fund managers' consensus wisdom in stock holdings under different market efficiency by examining the investment value and risk consequence of holdings concentration in large-cap and small-cap stocks. First, we find that stocks with concentrated hedge fund holdings earn higher future returns than those with lower holdings concentration. The holding period stock returns subsequent to the identified holdings concentration are persistently positive. Second, stocks with concentrated hedge fund holdings are associated with higher downside risks, and holdings concentration expedites the drop of stock performance, especially during financial crisis. In addition, large-cap stocks with higher holdings concentration are associated with hedge funds using lower leverage, whereas small-cap stocks are concentrated by hedge funds using relatively high leverage.

This paper helps us understand managers' skills in exploring information advantage by investigating information content based on the aggregate active holdings of hedge funds. Managers overweight a stock if he believes the stock will outperform and underweight it otherwise. Our results provide evidence that fund managers have skills to collect and process information under different market efficiency, and the information in an inefficient market is more valuable than that in an efficient market. Our results also show that fund managers are required to have higher skills to invest in an inefficient market, as stocks are less efficiently priced and are riskier than those in an efficient market.



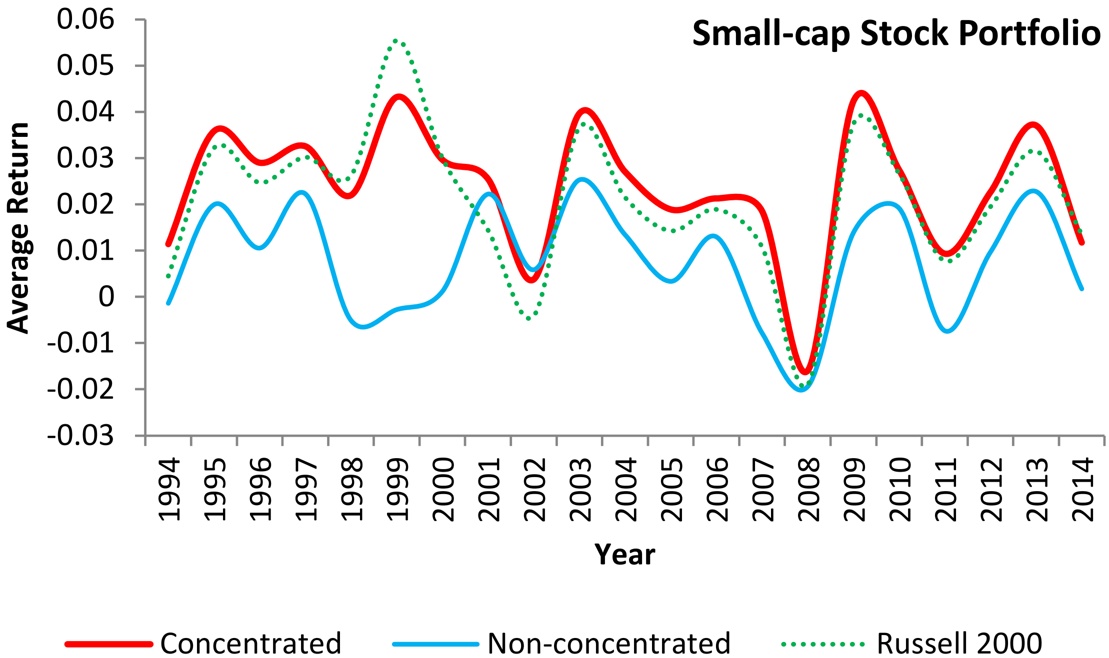


Figure 3.1: The average abnormal return of concentrated portfolio

The figure plots yearly average returns of the concentrated and non-concentrated portfolios for large-cap and small-cap stocks, respectively. Concentrated and non-concentrated portfolios refers to stock portfolio with the highest and lowest holdings concentration, respectively. The figure also plots yearly average returns of two benchmark portfolios: S&P 500 and and Russell 2000.

Table 3.1: Summary statistics of hedge fund stock holdings

This table presents summary statistics of hedge fund holdings in large-cap and small-cap stocks. The hedge fund data are from TASS hedge fund database and stock holdings data are from SEC 13F filings 1994-2014. Large-cap stocks (Panel A) refer to stocks in S&P 500 index, and small-cap stocks (Panel B) refer to stocks in Russell 2000 index. Benchmark refers to an index of hedge funds invest in a stock at the quarter end. Holdings concentration is defined as the aggregation of managers' active holdings and is measured by HC, OHC, and UHC, respectively. Panel C presents holdings concentration quintile ranked statistics for large-cap and small-cap stocks.

Panel A: Large-cap stocks (num of stocks: 723)

	Mean	Median	Std	Min	Max
Num of stocks held per fund	167	147	110	1	359
Holdings of a stock per fund ($bn)	0.0309	0.0021	0.2075	0.0000	55.1132
Holdings of all stocks per fund ($bn)	2.2405	0.1389	15.3360	0.0000	856.8256
Holdings of a stock in benchmark ($bn)	13.8766	6.6570	23.2989	0.0000	644.4171
Holdings of all stocks in benchmark ($tr)	4.9945	4.8393	2.3382	0.9462	10.3210
Holdings concentration (HC)	0.0007	0.0002	0.0035	-0.0155	0.0591
Holdings concentration (OHC)	-0.0005	-0.0019	0.0073	-0.0275	0.1455
Holdings concentration (UHC)	0.0007	0.0013	0.0021	-0.0373	0.0034

Panel B: Small-cap stocks (num of stocks: 3,856)

	Mean	Median	Std	Min	Max
Num of stocks held per fund	408	293	360	1	1268
Holdings of a stock per fund ($bn)	0.0082	0.0012	0.0344	0.0000	2.6165
Holdings of all stocks per fund ($bn)	0.2683	0.0220	1.6469	0.0000	94.9964
Holdings of a stock in benchmark ($bn)	0.4651	0.2770	0.5279	0.0000	9.4428
Holdings of all stocks in benchmark ($tr)	0.5604	0.5115	0.3240	0.1054	1.3216
Holdings concentration (HC)	-0.0007	-0.0015	0.0076	-0.1641	0.2273
Holdings concentration (OHC)	-0.0029	-0.0045	0.0126	-0.1972	0.1848
Holdings concentration (UHC)	0.0007	0.0007	0.0015	-0.0715	0.0102

Panel C: Holdings concentration quintile rank

	1	2	3	4	5
Large-cap stocks					
Holdings concentration (HC) %	-0.2835	-0.0708	0.0334	0.1588	0.5131
Stock weight in hedge fund %	1.2705	0.6764	0.7407	0.8791	1.4897
Stock weight in benchmark %	0.5715	0.2693	0.2571	0.2586	0.2852
Number of funds holding the stock	637	469	454	451	432
Small-cap stocks					
Holdings concentration (HC) %	-0.8206	-0.3029	-0.1411	0.0540	0.8368
Stock weight in hedge fund %	0.6637	0.5127	0.5175	0.7803	2.0439
Stock weight in benchmark %	0.0499	0.0515	0.561	0.0890	0.1873
Number of funds holding the stock	88	112	115	135	147

Table 3.2: Holdings concentration and edge fund characteristics

This table presents the characteristics of hedge funds invested in stock portfolios ranked by holdings concentration. The hedge fund characteristics include AUM_t (in millions), which is calculated as the sum of AUMs of all the hedge funds managed by a fund company at quarter t; $Big\ HFs$, which is calculated as the number of hedge funds with AUM greater than \$10 billion in each fund company; $Return_t$, which is calculated as the percentage change of the net asset values of the fund company between the beginning and the end of quarter t; $Return\ Std_t$, which is calculated as the standard deviation of the return of a hedge fund company in quarter t; Age_t (in months), which is calculated as the asset weighted average age of the managed hedge funds. Panel A and Panel B show the results for hedge funds holding large-cap and small-caps stocks, respectively. The last two rows report the mean difference of the characteristics of hedge funds holding stocks with the highest concentration and those with the lowest concentration and the p-value.

Panel A: For hedge funds holding large-cap stocks

Holdings Concentration (HC)	Num of HFs	AUM$_t$ (\$ M)	Big HFs	Return$_t$	Return Std$_t$	Age$_t$ (Months)
Low	236	2.195	0.006	0.017	0.026	72
2	253	2.033	0.005	0.018	0.026	73
3	265	1.926	0.004	0.019	0.027	74
4	266	1.848	0.003	0.020	0.028	76
High	268	1.622	0.003	0.023	0.030	79
High-Low		-0.573	-0.003	0.006	0.004	7
t-val		(-6.53)	(-3.85)	(4.73)	(8.12)	(3.20)

Panel B: For hedge funds holding small-cap stocks

Holdings Concentration (HC)	Num of HFs	AUM$_t$ (\$ M)	Big HFs	Return$_t$	Return Std$_t$	Age$_t$ (Months)
Low	226	2.100	0.019	0.016	0.027	57
2	241	1.945	0.014	0.019	0.027	60
3	264	1.868	0.012	0.021	0.028	63
4	268	1.796	0.010	0.021	0.028	65
High	273	1.774	0.009	0.022	0.029	67
High-Low		-0.326	-0.005	0.006	0.002	10
t-val		(-10.07)	(-3.95)	(6.16)	(9.67)	(2.98)

Table 3.3: Holdings concentration and subsequent stock returns

This table presents the subsequent stock returns on quintile portfolios sorted on the basis of holdings concentration of hedge funds. At the end of each quarter from 1994 to 2014, We sort stocks into quintiles in ascending order based on hedge fund holdings concentration and compute the average monthly equal-weight and value-weight portfolio returns in the subsequent quarter. Holdings concentration is measured using HC, OHC, and UHC, separately. We also present risk adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the portfolio performance using the DGTW (1997) characteristic adjustment. Stocks with price lower than $ 5 are excluded. Panel A and Panel B present the results using HC measure for large-cap and small-caps stocks, respectively. Panel C and Panel D present the results using OHC and UHC measure. The last two rows report the difference in mean abnormal returns for stocks with the highest concentration and those with the lowest concentration and the t-value. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: Large-cap stock portfolio

Holdings	Equal-weight portfolio returns %					Value-weight portfolio returns %				
Concentration (HC)	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha
Low	0.78	-0.02	-0.03	0.01	-0.02	0.80	0.34	0.25	0.25	-0.17
2	1.05	0.18	0.09	0.13	0.06	0.77	0.35	0.32	0.31	-0.12
3	1.10	0.38	0.28	0.29	0.17	0.80	0.55	0.56	0.55	0.02
4	1.24	0.49	0.42	0.43	0.25	0.83	0.60	0.64	0.63	-0.09
High	1.66	0.82	0.51	0.49	0.71	1.13	0.82	0.56	0.53	0.27
High-Low	0.88***	0.86***	0.55***	0.48***	0.75***	0.33***	0.48***	0.31	0.28	0.42***
t-val	(10.33)	(34.08)	(6.06)	(5.57)	(10.97)	(4.06)	(10.14)	(1.48)	(1.24)	(4.68)

Panel B: Small-cap stock portfolio

Holdings	Equal-weight portfolio returns %					Value-weight portfolio returns %				
Concentration (HC)	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha
Low	1.30	0.19	0.03	-0.14	0.34	0.48	0.21	0.21	0.17	-0.38
2	1.36	0.39	0.07	-0.11	0.26	0.59	0.68	0.43	0.03	-0.30
3	1.36	0.62	0.32	-0.05	0.26	0.77	1.01	0.72	0.82	-0.22
4	1.56	0.86	0.82	0.73	0.48	0.83	1.07	1.01	1.17	-0.14
High	1.78	1.11	1.27	1.20	0.74	0.92	1.03	0.87	0.83	0.07
High-Low	0.48***	0.92***	1.22***	1.34***	0.39***	0.41***	0.82***	0.66***	0.65***	0.45***
t-val	(6.50)	(11.09)	(8.11)	(4.75)	(8.57)	(6.76)	(9.99)	(3.88)	(3.89)	(5.06)

Table 2 - Continued

Panel C: Stock portfolio ranked by OHC

Holdings Concentration (OHC)	Large-cap stock return % Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha	Small-cap stock return % Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha
Low	0.81	-0.23	-0.28	-0.24	-0.07	1.52	0.15	-0.19	-0.40	0.39
2	1.04	0.20	0.13	0.17	0.09	1.36	0.41	0.15	-0.00	0.24
3	1.05	0.37	0.28	0.29	0.15	1.39	0.63	0.49	0.06	0.26
4	1.33	0.56	0.49	0.51	0.37	1.57	0.86	0.82	0.77	0.48
High	1.59	0.94	0.65	0.61	0.63	1.74	1.11	1.26	1.18	0.70
High-Low	0.78	1.17	0.93	0.85	0.70	0.22	0.96	1.45	1.58	0.31
t-val	(11.59)	(45.50)	(7.00)	(6.38)	(10.73)	(5.09)	(18.53)	(5.98)	(5.16)	(6.92)

Panel D: Stock portfolio ranked by UHC

Holdings Concentration (UHC)	Large-cap stock return % Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha	Small-cap stock return % Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	DGTW Alpha
Low	1.17	0.74	0.51	0.49	0.27	1.65	1.09	0.90	0.80	0.53
2	1.36	0.66	0.56	0.57	0.40	1.57	0.59	0.65	0.60	0.47
3	1.16	0.30	0.21	0.24	0.19	1.57	0.59	0.65	0.60	0.47
4	1.12	0.12	0.04	0.07	0.15	1.42	0.53	0.40	0.11	0.32
High	1.01	0.03	-0.04	-0.03	0.12	1.28	0.38	0.16	-0.05	0.24
High-Low	-0.16	-0.71	-0.55	-0.52	-0.39	-0.37	-0.71	-0.74	-0.85	-0.29
t-val	(-2.70)	(-9.07)	(-4.29)	(-3.95)	(-2.49)	(-9.31)	(-9.67)	(-3.28)	(-2.65)	(-6.67)

Table 3.4: Holdings concentration and cumulative stock returns

This table presents future cumulative risk-adjusted returns of concentrated and non-concentrated portfolios. Concentrated and non-concentrated portfolio refer to stock portfolio with the highest and lowest holdings concentration, respectively. For each stock, We calculate alpha as the difference between the stock return and the return of one of 125 benchmark portfolios that have comparable characteristics in size, book-to-market ratio, and past stock returns (DGTW, 1997). Starting from the end of month t, the cumulative DGTW alpha over 1, 2, 3, 6, 9, and 12 months are reported. In Panel A, the sample mean, mean difference, and t-value are presented for large-cap and small-caps stocks, respectively. Panel B shows quarterly DGTW alpha of long-short strategy that buy stocks in the concentrated portfolio and short stocks in the non-concentrated portfolio, implemented in the subsequent quarters Q1, Q2, Q3, and Q4. DGTW alpha deflated by alpha at current quarter (Q0) and t-value are also reported. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: concentrated vs non-concentrated

	Large-cap portfolio alpha %				Small-cap portfolio alpha %			
	Conc.	NConc.	Diff		Conc.	NConc.	Diff	
(t-1, t)	1.61	-0.82	2.45	***	1.69	-0.62	2.31	***
	(15.60)	(-7.55)	(17.01)		(23.34)	(-7.38)	(28.52)	
(t, t+1)	1.17	-0.39	1.56	***	1.22	-0.11	1.32	***
	(11.68)	(-4.25)	(11.82)		(18.60)	(-2.14)	(16.59)	
(t+1, t+2)	1.87	-0.52	2.39	***	1.97	0.12	1.85	***
	(13.25)	(-3.27)	(12.43)		(22.44)	(-0.64)	(16.20)	
(t+1, t+3)	2.04	-0.18	2.22	***	2.17	0.88	1.29	***
	(11.66)	(-0.67)	(9.63)		(21.47)	(3.74)	(9.08)	
(t+1, t+6)	2.29	0.42	1.87	***	2.75	2.67	0.00	
	(10.06)	(3.67)	(5.78)		(20.33)	(9.80)	(0.37)	
(t+1, t+9)	2.46	1.02	1.45	***	3.12	4.31	-1.19	***
	(9.90)	(4.94)	(4.95)		(18.45)	(12.94)	(-4.53)	
(t+1, t+12)	3.81	1.68	1.13	***	3.35	5.67	-2.32	***
	(10.09)	(5.73)	(4.75)		(17.34)	(14.86)	(-7.31)	

Panel B: long-short strategy

	Large-cap portfolio Alpha %				Small-cap portfolio Alpha %			
	Alpha	t-val	Alpha - $Alpha_0$	t-val	Alpha	t-val	Alpha - $Alpha_0$	t-val
M1 (t, t+1)	0.82***	(13.94)	-0.38***	(-5.21)	0.71***	(17.56)	-0.53***	(-8.20)
M2 (t+1, t+2)	0.39***	(6.81)	-0.81***	(-10.00)	0.28***	(6.97)	-0.91***	(-15.90)
M3 (t+2, t+3)	-0.12*	(-1.79)	-1.32***	(-16.15)	-0.21***	(-5.56)	-1.39***	(-24.84)
Q1 (t+1, t+3)	0.88***	(9.37)	-1.95***	(-9.96)	0.86***	(12.97)	-2.39***	(-13.58)
Q2 (t+4, t+6)	-0.21**	(-2.01)	-3.21***	(-17.12)	-0.98**	(-2.19)	-3.66***	(-24.08)
Q3 (t+7, t+9)	-0.18**	(-2.40)	-3.12***	(-15.87)	-0.29***	(-4.21)	-3.75***	(-25.03)
Q4 (t+10, t+12)	-0.15**	(-2.16)	-3.15***	(-14.98)	-0.32***	(-3.85)	-3.53***	(-23.26)

Table 3.5: Holdings concentration and risk analysis

This table shows time series average returns and risks of the portfolios with the concentration from low to high. At the end of each quarter, 5 portfolios of stocks are formed on the basis of hedge fund holdings concentration, weighted by the quarterly hedge fund stock holdings. At each month starting from January 1994, We use 60 month rolling windows of previous returns to estimate the risk measures of each portfolio. The risk measures include standard deviation, skewness, kurtosis, Value at Risk (VaR), expected shortfall (ES), and tail risk (TR), among which VaR, ES, and TR are calculated based on Cornish-Fisher (1937) in the following.

$$VaR(\alpha) = -(\mu + \Omega(\alpha) * \sigma)$$

$$ES_t(\alpha, \tau) = -E_t[R_{t+\tau} | R_{t+\tau} \leq -VaR_t(\alpha, \tau)]$$

$$TR_t(\alpha, \tau) = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau})^2 | R_{t+\tau} \leq -VaR_t(\alpha, \tau)]}$$

The table also presents the mean difference of returns and risks between high concentration and low concentration portfolios. Panel A and Panel B show the results for large-cap and small-caps stocks, respectively. The standard t-statistics and the Newey-West (1987) adjusted t-statistics are provided. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: Large-cap stocks

Holdings Concentration (HC)	Average Return %	STD	Skewness	Kurtosis	VaR	ES %	TR
Low	1.054	0.081	-0.038	1.440	0.118	0.871	0.041
2	1.086	0.087	-0.009	1.518	0.127	0.926	0.043
3	1.207	0.091	-0.011	1.445	0.132	0.956	0.045
4	1.355	0.096	-0.027	1.347	0.140	0.996	0.047
High	1.578	0.108	0.063	1.499	0.152	1.109	0.052
High-Low	0.524***	0.028***	0.102***	0.059***	0.034***	0.238***	0.012***
Standard t-stat	(45.63)	(54.80)	(11.12)	(7.99)	(47.67)	(33.30)	(47.10)
Newey-West t-stat	(21.84)	(25.74)	(5.38)	(3.92)	(22.73)	(15.91)	(22.33)

Panel B: Small-cap stocks

Holdings Concentration (HC)	Average Return %	STD	Skewness	Kurtosis	VaR	ES %	TR
Low	1.063	0.097	0.245	1.844	0.136	1.025	0.046
2	1.266	0.104	0.170	1.519	0.146	1.083	0.050
3	1.433	0.108	0.180	1.403	0.150	1.120	0.052
4	1.609	0.111	0.200	1.442	0.152	1.138	0.052
High	1.756	0.115	0.263	1.727	0.154	1.175	0.054
High-Low	0.693***	0.018***	0.022***	-0.116	0.018***	0.150***	0.008***
Standard t-stat	(73.82)	(52.50)	(6.67)	(-1.67)	(37.02)	(31.31)	(46.30)
Newey-West t-stat	(35.24)	(24.64)	(3.20)	(-0.82)	(17.53)	(14.95)	(21.86)

Table 3.6: Decrease of stock returns in crisis and normal periods

This table presents quarterly decrease of stock returns during crisis periods and normal periods. The expected decrease of stock returns ΔR_{t+1} is calculated as the difference between the stock return at quarter $t+1$ and the stock return at quarter t. The crisis periods include 2001 and 2007 Q4 - 2009 Q1. Stocks with Carhart ΔR_{t+1} less than zero are included in our sample. Panel A and Panel B present the results using HC measure for large-cap and small-cap stocks, respectively. The last two rows report the difference in mean leverage for hedge funds holding the stocks with the highest concentration and those with the lowest concentration and the t-statistics. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: Large-cap stock portfolio

	(%) $\Delta R_{t+1} = R_{t+1} - R_t$							
	Crisis period				Normal period			
	Conc. (1)	NConc. (2)	Diff (1)-(2)	t-val	Conc. (3)	NConc. (4)	Diff (3)-(4)	t-val
Raw return	-4.43	0.57	-5.01***	(-3.38)	-3.56	-0.43	-3.13***	(-7.77)
CAPM alpha	-1.41	-0.91	-0.50***	(-3.62)	-1.29	-0.90	-0.39***	(-7.42)
FF alpha	-3.31	-0.89	-2.41**	(-2.00)	-2.11	-1.11	-1.00*	(-1.93)
Carhart alpha	-4.97	-2.29	-2.68**	(-2.21)	-3.61	-2.58	-1.02***	(-13.81)
DGTW alpha	-5.02	-2.11	-2.91**	(-2.07)	-3.42	-0.22	-3.20***	(-7.81)

Panel B: Small-cap stock portfolio

	(%) $\Delta R_{t+1} = R_{t+1} - R_t$							
	Crisis period				Normal period			
	Conc. (1)	NConc. (2)	Diff (1)-(2)	t-val	Conc. (3)	NConc. (4)	Diff (3)-(4)	t-val
Raw return	-3.95	0.28	-4.23***	(-4.55)	-3.68	-0.48	-3.19***	(-12.47)
CAPM alpha	-2.05	-1.20	-0.85***	(-3.56)	-2.48	-1.75	-0.73***	(-3.84)
FF alpha	-4.79	-1.75	-4.05***	(-5.10)	-4.32	-3.09	-1.23***	(-3.01)
Carhart alpha	-7.84	-4.06	-3.78***	(-5.98)	-8.71	-7.38	-1.33	(-1.30)
DGTW alpha	-6.48	-2.32	-4.16***	(-4.21)	-3.14	-0.41	-2.73***	(-9.79)

Table 3.7: Holdings concentration and hedge fund leverage

This table presents the relationship between hedge fund leverage and the holdings concentration. We use three measures for leverage: the ratio of 13F equity holdings to hedge fund AUM, the number of big prime brokers, and the average leverage of a hedge fund company. Panel A and Panel B present the results for large-cap and small-caps stocks, respectively. Sample means are presented for stock portfolios sorted by holdings concentration. The last two rows report the difference in mean leverage for hedge funds holding the stocks with the highest concentration and those with the lowest concentration and the t-statistics. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

Panel A: Large-cap stocks

Holdings Concentration (HC)	13F equity holdings/AUM	Num of big prime brokers	Average leverage
Low	0.025	0.974	3.399
2	0.025	0.961	3.021
3	0.026	0.958	2.927
4	0.027	0.947	2.773
High	0.027	0.939	2.612
High-Low	0.002***	-0.035***	-0.787**
t-val	(3.02)	(-10.171)	(-2.55)

Panel B: Small-cap stocks

Holdings Concentration (HC)	13F equity holdings/AUM	Num of big prime brokers	Average leverage
Low	0.032	0.918	2.895
2	0.029	0.950	3.207
3	0.024	0.956	3.401
4	0.022	0.966	3.321
High	0.018	0.956	3.171
High-Low	-0.014***	0.038***	0.276**
t-val	(-6.94)	(3.66)	(2.43)

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