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Essays on mutual fund performance and conflict of interest

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ESSAYS ON MUTUAL FUND PERFORMANCE AND CONFLICT OF INTEREST

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To my parents, my wife Ann, my son Kevin, and my daughter Yaya.

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ABSTRACT

In this dissertation, I address two main topics regarding mutual fund. One is performance persistence in general, and the other is conflict of interest for investment bank-affiliated mutual funds.

The first chapter examines the concentration of active mutual fund managers' research efforts toward information-intense stocks and the degree to which they are successful in such efforts. We show that funds that hold stocks with high information intensity exhibit large performance dispersion, indicating that both skilled and unskilled fund managers are attracted to such stocks. Moreover, the performance of these funds is predictable by fund skill proxies such as past fund alphas, and the well-known phenomenon of performance persistence is only observed among funds with high information intensity. The effect of fund information intensity on performance persistence is robust to the control of characteristics of fund holdings such as market cap, illiquidity, and return volatility, and is different from the effect of existing measures of fund activeness. Finally, information intensity increases fund flow sensitivity to past performance. These findings suggest that, with costly information production, information intensity is an important dimension of active investment decisions by fund managers and an important dimension of fund selection decisions by investors.

The second chapter examines the conflict of interest in IPO share allocations by investment banks and by fund management companies. Affiliated mutual funds successfully avoid cold IPOs. However, they are “crowded out” of hot IPOs -- the IPO shares they do receive are inversely related to the hotness of the IPOs. Within affiliated

fund families, funds with larger size, higher expense ratio, and higher past returns are more likely to receive IPO shares. However, these funds receive less allocations for hotter IPOs. Overall, my findings present a more complicated picture to the conflict of interest in IPO share allocations than suggested by prior studies.

The third chapter examines the relation between mutual fund turnover and performance persistence. Existing studies have reported mixed empirical relations between portfolio turnover and mutual fund performance. This paper documents strong heterogeneity in the turnover-performance relation, which helps reconcile the contrasting evidence in prior studies. While there is no significant relation between turnover and fund performance on average, performance is particularly dispersed among high-turnover funds. Further, performance persistence is much stronger among funds with higher turnover. These findings are consistent with the notion that turnover is persistently and positively related to performance for some fund - possibly due to the fact that turnover is driven by available investment opportunities, while persistently and negatively related to performance for other funds - possibly due to high trading costs associated with high turnover. Finally, we find that the relation between turnover and performance persistence is largely a cross-sectional effect, not a time-series effect.

PUBLIC ABSTRACT

Mutual fund serves as an important investment vehicle for the general public in the US. Thus, how to evaluate the skills of fund managers becomes tantamount to mutual fund investors. In this thesis, I examine and discuss two potential attributions of fund performance. The first one is the information intensity of fund portfolio holdings. I found that the more information-intense stocks held in a fund portfolio, the more likely the fund will outperform in the near future. The second one is the frequency of trading. Skillful fund managers are more likely to seek out profitable investment opportunities and trade on them, thus deliver positive risk-adjusted returns in the near future. Both measures are easy to calculate and could be added into investors' arsenal for picking winning funds.

Another part of my thesis examines potential conflict of interest of investment bank-affiliated mutual funds in terms of IPO allocations. I found that investment banks do favor their affiliated mutual funds by allocating hot IPOs rather than cold IPOs. But due to popularity of hot IPOs, the amount allocated to affiliated mutual funds is small. It is not enough to boost the funds' performance.

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Chapter 1
Costly Information Production, Information Intensity, and Mutual Fund Performance

1.1 Introduction

In oil exploration, prospectors must first narrow down the promising locations before they start their costly drilling operations. Much the same can be said about information production in the stock market. When stock selection information is scarce, investors have to be smart about where to deploy their costly efforts and limited resources in their search for information.

Such decisions are important in today's market, where investment managers increasingly rely on costly information to generate performance. Consider the evolution of fundamental research, the most popular approach used by equity mutual fund managers to produce stock selection information. The traditional form of fundamental research, espoused as early as by Graham and Dodd (1934), involves parsing publicly available information such as corporate financial statements to identify undervalued stocks. The cost of performing such research during recent decades has become relatively low and, perhaps as a result, its potential rewards appear to be disappearing. Over time, the focus of fundamental research has shifted toward uncovering information not yet publicly available. For example, many fund managers engage in "channel-checking", i.e., gathering information about a company (e.g., Apple) by talking to its suppliers and customers.[1] Some fund managers rely on interactions with corporate executives (e.g., face-to-face talks or conference calls) to assess

[1] Similar to channel-checking, investors have also attempted to obtain information from franchisees about franchising companies such as McDonald's. Anecdotally, some funds send analysts to count the lights of hotel rooms at night, or to count the cars parked outside shopping malls, in order to predict the revenues of hotels and department stores.

their professional qualities and incentives, and to capture "soft" information not apparent from reading financial statements or news releases.[2] Indeed, several investment firms (e.g., Fidelity) attempt to derive competitive advantage from having large troops of analysts who frequently visit firms and meet with corporate managers. Such efforts to uncover non-public information are considerably more costly than poring over financial statements.

Costly information production is rewarded in the efficient-market equilibrium described by Grossman and Stiglitz (1980).[3] In today's market, the effectiveness of such information production efforts could well be the deciding factor of investment performance. However, fund manager efforts, and the associated costs, are either unobservable or difficult to quantify, which perhaps explains why, so far, there is no direct empirical mechanism to examine their private-information production.[4]

In this study, we focus on a key decision in mutual fund costly information production – how fund managers allocate their research efforts across stocks. We ask: do skilled fund managers concentrate their research on stocks that are informationally intense, so that their research efforts are more likely to be rewarded? Further, are fund managers that aggressively pursue information-intense stocks successful in producing information and delivering performance? And, if so, how do we characterize their information production processes?

[2]For example, according to a recent Barron's report (Bary 2015), Fidelity Contrafund manager William Danoff talks to over 1000 corporate managers a year.

[3]In equilibrium, the expected return of the marginal information gatherer just equals the cost of gathering such information. An investor with more cost-effective information production technique than the marginal investor, however, may reap positive net present value from their information production efforts.

[4]Two recent studies indirectly showcase the importance of private-information production by fund managers. Wermers, Yao, and Zhao (2012) find that stock selection information extracted from the portfolio holdings of skillful fund managers has a low correlation with a set of public signals – stock characteristics indicative of mispricing – but is significantly related to future corporate earnings. They conjecture that successful fund managers generate their own private information about future corporate fundamentals. In addition, Kacperczyk and Seru (2007) show that funds relying more on analyst recommendation changes – a source of public information – have worse performance, implying that such managers have less private information to rely upon.

These are relevant questions for fund managers and for fund investors. The active investment management industry faces serious challenges in coming up with valid investment strategies, and fund investors face an ever shrinking pool of active investment managers who can deliver consistent performance (Barras, Scaillet, and Wermers, 2010; Fama and French, 2010).

We quantify the potential reward to private-information production using a measure of information intensity, or a stock's tendency to produce large surprises to investors when significant corporate events or news arrives. Such events include, for example, earnings announcements, mergers and acquisitions, product launches or failures, and executive turnover. Intuitively, if certain information causes a large investor surprise, it should be valuable to obtain beforehand. Note that this notion of information intensity is different from the concept of mispricing, which is defined relative to public information.[5]

To measure large information surprises and information intensity, we draw on the literature of nonparametrically estimating stock price jumps (e.g., Barndorf-Nielsen and Shephard, 2006). Specifically, the information intensity of a stock is the proportion of total stock return variance attributable to jumps. This measure can be intuitively understood as the amount of significant information relative to the total amount of available information and noise combined.[6] Further, we quantify the information intensity of a fund portfolio based

[5]In addition, the information intensity measure should be technically better than traditional proxies for mispricing in quantifying potential rewards to information production. Traditional mispricing proxies, such as illiquidity and firm size, are based on market frictions. But high frictions in the form of information costs or trading costs could overwhelm any expected reward to information, defeating the purpose of measuring the reward.

[6]The relation between stock price jumps and significant corporate events has been documented in existing studies; see, for example, Lee and Mykland (2008), Lee (2012), and Jiang and Yao (2013). Although, conceptually, both information and noise could cause large price movements, these studies show that most stock price jumps are related to significant corporate events or macroeconomic news.

on the weighted average of the stock-level information intensity across the fund's stock holdings. A high level of fund information intensity suggests that the fund aggressively invests in information-intense stocks.

We perform analysis on a large sample of U.S. equity mutual funds over the period from 1980 to 2014. We show that the information intensity (hereafter "II") of a fund is related to various fund characteristics indicative of investment activeness. For example, funds with higher II tend to be younger, smaller, trading more frequently and charging higher fees. They also tend to have higher ActiveShare (Cremers and Petajisto, 2009). Furthermore, fund II is highly persistent over time, suggesting that high information intensity is likely related to the conscious efforts by funds, rather than due to random chance.

Stocks with high information intensity represent opportunities for skilled active fund managers. But can funds successfully produce information on these stocks? We conjecture that high-II stocks may attract all sorts of active funds, not all of them having the necessary skills to produce stock-selection information. That is, among high-II funds, only those that are skilled have the potential to deliver good performance. Indeed, our analysis shows that fund II, per se, does not predict performance. However, among high-II funds, there is a particularly large dispersion in performance, and such performance differences are highly predictable by fund skill proxies, such as past fund alphas. For example, among funds ranked in the top II quintile, those in the top quintile of past four-factor alpha subsequently generate a significantly positive after-expense monthly four-factor alpha of 0.20%, while those in the bottom past four-factor alpha quintile generate a significantly negative monthly four-factor alpha of -0.25%. Their performance difference, 0.448% per month, or, equivalently 5.376% per year, is both economically and statistically significant. Moreover, an interesting contrast is that, among funds in the bottom II quintile, past fund alphas do not significantly predict subsequent performance. That is, the well-known phenomenon of performance persistence is concentrated among high-II funds.

We extend the analysis in several dimensions to gain further perspectives on the effect of fund information intensity. First, we show that the results are robust to alternative fund performance measures such as fund net returns and the characteristics selectivity measure of Daniel, Grinblatt, Titman, and Wermers (1997), to the use of alterative proxies for fund skills such as the similarity-based fund performance measure of Cohen, Coval, and Pastor (2006) and the return gap measure of Kacperczyk, Sialm, and Zheng (2008), and to the use of fund information intensity measures lagged by as many as four quarters.

Second, we compare the effect of fund information intensity on fund performance with several competing effects of fund characteristics, including the effect of the return volatility of fund holdings, the effect of fund investments in small and illiquid stocks, and the effect of fund activeness. Our key findings are highlighted below.

a) Stock return volatility. Since the measure of information intensity relies on a particular decomposition of stock return volatility, we are curious about how the effect of information intensity differs from the effect of stock return volatility. We find that funds holding more volatile stocks tend to have worse performance, consistent with the recent findings of Jordan and Riley (2015). However, the negative relation between fund stock holdings' return volatilities and fund performance mainly exists among potentially unskilled funds, i.e., funds with poor past alphas. Among potentially skilled funds (i.e., those with good past alphas), the return volatility of stock holdings does not predict performance. In contrast, the effect of information intensity is mainly observed among potentially skilled funds.

That is, among funds with high past alphas, those with higher II exhibit significantly better performance, but among funds with low past alphas, II does not predict performance. This contrast suggests that the relation of fund performance with the volatility of fund stock holdings is not driven by fund decisions to produce costly information, but rather has a different underpinning – for example, preference for lottery-like stocks.[7]

b) Market frictions. Although we argue that information intensity is conceptually different from misvaluation of stocks relative to public information, empirically information intensity may have an intricate relation with various forms of market frictions that are indicative of mispricing. On the one hand, stocks with large frictions, such as small stocks and illiquid stocks, tend to be neglected stocks and thus are more likely to cause large surprises when they have significant news. On the other hand, investors could experience large surprises for reasons unrelated to market frictions. For example, to avoid competition a firm may provide little voluntary disclosure but instead release a large amount of information at the time of mandatory disclosure (e.g., earnings announcements). Therefore, it is interesting to see to what extent the information intensity effect on fund performance is related to, and different from, the effect of market frictions. Using both a sorted portfolio approach and multivariate regressions, we show that the effect of information intensity on fund performance persistence is not subsumed by fund tendency to invest in small and illiquid stocks.

c) Fund activeness. Several recent mutual fund studies have examined the activeness of fund investment strategies, where fund activeness is measured by the departure of either

[7]Stocks with high volatility tend to have positively skewed returns, therefore may attract managers with lottery preferences. Such stocks may be particularly appealing to managers with tournament-like incentives (e.g., Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; and Huang, Sialm, and Zhang, 2011).

fund portfolio weights or fund returns from those of the benchmark portfolios (Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; Cremers, Ferreira, Matos, and Starks, 2015). While active funds may engage in strategies that exhibit both large departure from benchmarks and high information intensity in their stock holdings, we find that the relation of information intensity with fund performance is different from that of two activeness proxies in the existing literature that measure departure from benchmarks – ActiveShare and fund return R2. After controlling for these activeness measures using either the sorted portfolio approach or multivariate regressions, we find that the effect of information intensity on performance persistence remains significant. Thus, relative to departure from benchmarks, information intensity captures another important dimension of active investment strategies, which could be valuable in guiding the fund selection decisions of investors.

Third, we look into the nature of information that skilled high-II funds are able to produce. We focus on two types of corporate events – earnings announcements and M&A announcements. Previous studies have shown that such events often lead to large investor surprises. Further, the importance of the ability in predicting corporate earnings to fund performance has also been documented in existing studies (e.g., Baker, Litov, Watcher, and Wurgler, 2010; Jiang and Zheng, 2015). We find that funds with high past alpha and high II have substantially higher returns during the short windows around these corporate events, relative to funds with high past alpha but low II, or relative to funds with high II but low past alpha. This provides corroborative evidence that skilled funds successfully uncover private information from information-intense stocks, and that earnings and M&A events are the relevant types of private information these funds successfully uncover.

Finally, we examine the behavior of fund flows to see if fund investors take information intensity into account when they make fund investment decisions. We find that the relation of fund flows with past performance is significantly more sensitive among those high-II funds, than among those low-II funds. This result is robust to the control of various fund characteristics, including the effect of fund investments in small stocks and illiquid stocks, the volatility characteristics of fund holdings, and the effect of fund activeness. Thus, it seems that investors' fund selection decisions are affected by how fund managers allocate their costly information production efforts and the impact of such allocation on fund performance.

The rest of the paper is organized as follows. Section 1.2 introduces the measure of information intensity at both the stock level and at the fund level. Section 1.3 describes data. Section 1.4 presents the empirical results. Section 3.5 concludes.

1.2 Measuring Information Intensity

An informationally-intense stock is one that is likely to cause large surprises to investors. Various factors can affect the level of information intensity. Some firms' business operations are more uncertain in nature than others – for example, the operating performance of technology companies is typically more unpredictable than that of utilities companies. Also, some firms may hold off voluntary disclosure until the time of mandatory disclosure (e.g., earnings announcements), at which time they lease information in lump sum. Alphabet (Google), Coke-Cola, AT&T, and Costco are well-known examples of firms withholding earnings guidance. Information intensity is also likely related to market frictions – for stocks with higher information costs or trading costs, there is likely more information out there not fully impounded into stock prices, resulting in investor surprises when such information ultimately arrives in a conspicuous way, e.g., via corporate announcements. It is likely that these factors interact with each other to shape up the level of information intensity of a stock.

In econometric terms, these large surprises are represented by stock price jumps – large discrete movement in stock prices. Various econometric methods have been developed to identify jumps in asset prices or to quantify the statistical properties of jumps. The estimation techniques range from maximum likelihood, GMM, Bayesian, to non-parametric. In this study, we use the non-parametric approach developed in the recent literature (e.g., Barndorff-Nielsen and Shephard, 2004 and 2006) to estimate the contribution of jumps to overall stock return variance. The idea behind this approach is that a quantity known as bi-power variation represents the contribution by the continuous diffusion component of stock price movement to the stock return variance, while the remaining variance can then be attributed to the jump component. Specifically, consider a general, continuous-time, jump-diffusion process for stock price:

$$\frac{dS_t}{S_t} = \mu_t dt + \sigma_t dW_t + dJ_t \tag{1}$$

where μ_t is the instantaneous drift, σ_t is the instantaneous diffusion volatility, dW_t is a standardized Brownian motion, J_t is a pure jump Lévy process with increments $J_t - J_s = \sum_{s \leq \tau \leq t} \kappa_\tau$, and κ_τ is the jump size. Suppose the stock prices are observed altogether N+1 times at discrete times n, with n = 0, 1, ..., N. The discretized log-return from time n-1 to n is then $r_n = ln(S_n) - ln(S_{n-1})$, for n=1, ..., N. Define the *realized variance* as

$$\text{RV} = \sum_{n=1}^{N} r_n^2 \tag{2}$$

And the *bi-power variation* is defined as

$$\text{BPV} = \frac{\pi}{2}\frac{N}{N-1}\sum_{n=2}^{N} |r_n||r_{n-1}| \tag{3}$$

The bi-power variation measure is similar to the realized variance measure, except that the quadratic term of return r_n^2 in RV is replaced by by the product term of the absolute values of two consecutive-observed returns, $|r_n||r_{n-1}|$, in BPV. The key idea is that the diffusion volatility affects the magnitude of both r_n and r_{n-1}, while a jump may have a large impact on either r_n or r_{n-1}, but not both. Thus, in the limit, BPV is not affected by jumps. Indeed, under reasonable assumptions, as data sampling frequency increases, i.e., N $\rightarrow \infty$, the discretely sampled RV and BPV converge respectively to the continuous-time measures of integrated variance and integrated diffusion variance. For notional convenience, we normalize the time span so that t∈[0,1]. We have,

$$\lim_{N\rightarrow\infty}\text{BPV} \rightarrow \int_{t=0}^{1} \sigma_t^2 dt \tag{4}$$

$$\lim_{N\rightarrow\infty}\text{RV} \rightarrow \int_{t=0}^{1} \sigma_t^2 dt + \sum_{j=1}^{K} \kappa_j^2 \tag{5}$$

where K is the total number of jumps during the period and κ_j is the size of the j-th jump.

Now define the jump variance as JV=Max(0, RV-BPV).[8] It is easy to see that

$$\lim_{N\to\infty}\text{JV} \to \sum_{j=1}^{K} \kappa_j^2 \tag{6}$$

That is, JV is a consistent estimator of the contribution of pure jumps to the integrated variance. Further, the ratio JV/RV can be interpreted as the percentage contribution of jumps to the total return variance. Both JV and the ratio JV/RV have been used in existing studies to test the presence of jumps. See, e.g., Barndorff-Nielsen and Shephard (2004 and 2006), Andersen, Bollerslev, and Diebold (2004), and Huang and Tauchen (2005).[9]

In this study, we define the information intensity of a stock based on the ratio:

$$\text{SII} = \frac{\text{JV}}{\text{RV}} \tag{7}$$

We estimate the information intensity following the above equation (7) for each individual stock every quarter, using daily stock returns from CRSP for the period from 1980 to 2014. RV and BPV are estimated following equations (2) and (3) respectively. It is noted that many studies (with the exception of Jiang and Yao, 2013) estimate jumps using the intra-day data. We focus on daily data in our study for two reasons. First, intra-day data are not available for the earlier half of our sample period. Second, intra-day stock returns are known to subject to severe market microstructure effect. Christensen, Oomen and Podol-

[8] RV-BPV is non-negative in the continuous limit, but may be negative in the discrete-time estimates. Here we replace the negative estimate of RV-BPV by zero. Our results are not substantially altered if we simply define JV as RV-BPV.

[9] An alternative non-parametric approach for jump identification is based on the variance swap idea (e.g., Jiang and Oomen, 2008; Jiang and Yao, 2013). The variance swap approach identifies jumps based on their contributions to the return skewness instead of return variance.

skij (2014) show that jumps in asset prices are far less as frequent as suggested by tests based on high-frequency data. Many intra-day large returns are simply the effect of market microstructure noise or illiquidity and are often quickly reversed. By contrast, our main interest is on stock price jumps associated with important informational events. If a jump only has impact on stock return at the intra-day level but does not affect daily return with economically significant magnitude, it is not important for the purpose of this study.

After obtaining estimates of information intensity SII_{it} for each stock i during each calendar quarter t, we measure the information intensity of fund j during quarter t as:

$$\text{QII}_{jt} = \sum_{i=1}^{N_j} w_{ijt-1} \text{SII}_{it} \tag{8}$$

where N_j is the number of stocks held by fund j, and w_{ijt-1} is the weight of stock i in all of fund j's equity holdings at the beginning of a quarter (or the end of the previous quarter). That is,

$$w_{ijt-1} = \frac{V_{ijt-1}}{\sum_{i=1}^{N_j} V_{ijt-1}} \tag{9}$$

where V_{ijt} is the dollar value of fund j's holding of stock i in quarter t.[10]

In any given quarter, a fund may have high or low information intensity due to either its intentional pursuit of certain investment strategies or random chance. To reduce the influence of random chance, we further take the rolling four-quarter average of the quarterly-

[10] We have performed analysis using an alternative QII definition where the beginning-of-quarter weight w_{ijt-1} is replaced by the end-of-quarter weight w_{ijt} in the above expression. The results we obtain are quite similar. Intuitive, this is due to the fact quarterly fund turnover is relatively low, and the fact that at the stock level, SII is quite persistent over time.

measured fund information intensity:

$$\mathrm{II}_{jt} = \sum_{s=0}^{3} \mathrm{QII}_{jt-s} \tag{10}$$

We require at least two QII observations for the above II estimate to be valid.

1.3 Mutual Fund Data and Sample

The data on mutual funds are from two sources – CRSP and Thomson Reuters. Our sample includes actively-managed US domestic equity funds during the period from 1980 to 2014. The Thomson-Reuters data provide quarterly snapshots of mutual fund portfolio holdings. The CRSP database reports fund net returns, flows, investment objectives and other fund characteristics. Funds in these two datasets are matched via the MFLINKS file (available from Wharton Research Data Services, WRDS). We combine multiple share classes of a fund in the CRSP database into a single portfolio (value-weighted, based on beginning-of-quarter total net assets of each share class) before matching the CRSP data with the Thomson-Reuters data. Our focus is on the U.S. actively managed diversified equity funds that mainly invest in domestic stocks. We exclude index funds, international funds, municipal bond funds, bond and preferred stock funds, and sector funds. To ensure data accuracy, we exclude fund-quarter observations if a fund has less than 10 stock holdings with valid SII measures, and fund-quarter observations when the value of stock holdings with valid SII measures is less than 50% of the portfolio value. We further exclude fund-quarter observations if the total net assets are below $10 million dollars. We address the incubation bias (e.g., Evans 2010) by removing fund-quarter observations prior to the first offer date of the earliest share class of a fund reported in CRSP.

Funds report holdings at the end of their fiscal quarter (as indicated by the variable "rdate" in the Thomson data), which may not always be the end of a calendar quarter. In order to facilitate cross-sectional comparison, if the date of the reported holdings is not at a calendar quarter end, we assume that the holdings remain valid at the end of that calendar quarter, with adjustment for stock splits using the CRSP share adjustment factor. In addition, SEC's mandatory reporting frequency of mutual fund holdings is quarterly prior to 1985, semi-annual between 1985 and May 2004, and quarterly again afterwards. When a fund reports holdings at the semi-annual frequency and for the quarter it does not report its holdings, we assume that its holdings are the same as in the prior quarter.

Our final sample includes 3,348 unique funds and 159,480 fund-quarter observations during the 35-year period. Table 1.1 provides summary statistics for the mutual fund sample. For each sample year, we report the number of funds, the averages of the numbers of stocks held, the net assets (TNA), expense ratio, turnover, and the information intensity measure II. These numbers are as of the end of each year, and if in a given year, a fund ceases to exist in the data before the end of the year, we use its latest available information during that year. In 1980, the beginning of our sample, there are 216 funds, holding an average of 57 stocks per fund, with an average TNA of $192 million, an average expense ratio of 0.96% and an average annual turnover of 70%. By the end of the sample period, in 2014, there are 1,594 funds in the sample, holding 129 stocks on average, with an average TNA of $2.51 billion, an average expense ratio of 1.09% and an average turnover of 64%. The growth in the number of funds and the average TNA reflect the growth of the fund industry. The average fund TNA peaks in 2014. Before that, it peaked in 2007 and then took a large toll during the recent financial crisis of 2008 (and in 2002, after the burst of the internet bubble). By contrast, the number of funds does not fluctuate as dramatically around the crisis. The declining number of funds toward the end of the sample period is likely due to the time lag by Thomson-Reuters in updating the data.

The table also reports the cross-fund mean and standard deviation of our key variable of interest, fund information intensity (II). The average II hovers above 8% in the 1980s, drops below 8% during the early 1990s, late 1990s and early 2000s. It starts to pick up afterwards, reaching above 10% in the seven of the last 10 years of the sample period. Note that at the stock level, information intensity can be interpreted as the proportion of jump-induced variance in total stock variance. Thus, a 10% II at fund level means that on average, 10% of the return variances of stocks held by funds are due to jumps, or large information surprises. The cross-sectional standard deviation of II is more stable, but follows a similar pattern of time variation – it started high in the 1980s, trended lower in the 1990s and picked up again in recent years. In fact, the time series correlation between the mean and standard deviation of II is 51% during the 35-year sample period.

1.4 Empirical Results

1.4.1 Information Intensity and Fund Characteristics

We first attempt to understand the fund-level information intensity by relating it to various fund characteristics. In each quarter, we sort funds into quintiles based on its rolling four-quarter measure of information intensity II, and report the average characteristics for each fund quintile. In Panel A of Table 1.2, we first check the following characteristics: fund information intensity II, the weighted average of JV, RV, and return standard deviation (during the past 12 months) of stocks held by funds. The average information intensity of the funds ranked in the top quintile of II is 11.77%, suggesting that among the stocks they hold, over 11% of stock return variance is realized in the form of large surprises. By contrast, large surprises only account for 6.87% of return variances for stocks held by funds ranked in the bottom II quintile. That is, the information intensity of top-II fund quintile is almost twice as high as that for the bottom quintile, indicating a large cross-sectional variation. In addition, the weighted average JV, RV, and return standard deviation for stocks held by funds in the top II quintile are also much higher than those for stocks held by funds in the bottom II quintile. This suggests that high-II funds invest in highly-volatile stocks; and more importantly, they invest in stocks that tend to generate large surprises.

In the same panel, we then look at two characteristics indicative of fund activeness: ActiveShare and R2. The measure of ActiveShare follows Cremers and Petajisto (2009) and the measure of R2 follows Amihud and Goyenko (2013).[11] Going from bottom to top II quintiles, ActiveShare increases monotonically, with a large difference between the top and bottom quintiles. This supports the notion that stocks with more intense information attract more active funds. The relation between II and R2, however, is virtually flat and not monotonic.

Panel A of Table 1.2 further reports the number of stocks held by funds and fund turnover. These two measures are related to the concentration of fund holdings and the intensity of fund trading, which to some extent are also related to fund activeness. The average number

[11] We thank Martjin Cremers for providing the ActiveShare data. The data on ActiveShare we obtain are for the period from 1981 to 2012. Thus, the analysis involving this variable is for that period. R2 is the R-square of regressing monthly fund returns during the past 24 months onto the Carhart (1997) four factors.

of stocks held by funds increases from 75 for the bottom II quintile to 102 for the fourth quintile, and drops to 99 for the top II quintile. Fund portfolio turnover exhibits a similar pattern – turnover increases from the bottom to the fourth II quintile, but drops off for the top II quintile. In other words, both low-II and high-II funds are more concentrated and trade less, and the relations of II with holding concentration and trading activeness are not monotonic.

Panel B of Table 1.2 shows that funds with higher information intensity are smaller, younger, and charge higher fees. These characteristics also fit the profile of more active funds. The panel also reports the investment styles of funds in terms of size, book-to-market ratio, momentum, and illiquidity of stocks held by funds. The four style scores, SIZESCORE, BMSCORE, MOMSCORE, and ILLIQSCORE, are measured in the following way. First, we cross-sectionally standardize four stock-level characteristics – market-cap, book-to-market ratio, past 12-month returns, and the Amihud illiquidity ratio – across all stocks in a given quarter by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. We then take the weighted average of the standardized stock characteristics across the stocks held by a fund. The table shows that funds with higher II ranks hold more small stocks and illiquid stocks. But the relations of II with the value and momentum styles appear relatively weak.

Funds may have high IIs either due to their decisions to engage in private-information production, or due to sheer random chance. Fund IIs should be more persistent in the former case. Table 1.3 shows the averaged II during the subsequent four years after initial fund ranking, across the II quintiles. The persistence in information intensity is clear. For funds initially ranked in the top II quintile, their average II experiences a slight drop, from 11.77%

at the initial ranking (reported in Table 1.2) to 11.61% during the subsequent year, but stays above 11% throughout the five years after the ranking. For funds initially in the bottom quintile, their average II increases from 6.87% at the initial ranking (reported in Table 1.2) to 7.71% during the first year, and continues to rise slightly each year, until it reaches 8.58% in year 5. It is noteworthy that by year 5, the difference in II between the initially-ranked top and bottom fund quintiles remain large (11.08% vs. 8.58%). Such persistence suggests that a substantial component of II is due to their stable, long-term, information production efforts.

1.4.2 Information Intensity and Performance

The empirical relations between information intensity and various fund characteristics suggest that active funds are attracted to information-intense stocks. However, the information intensity measure only captures the opportunities for fund information production. It does not yet tell us whether funds are successful in turning these opportunities into valid stock selection information. Discovering non-public information about corporate fundamentals is not mechanical work; it requires skills. Thus, we expect that skills matter particularly for the performance of funds investing in information intense stocks. To test this prediction, we examine the effect of information intensity on fund performance and performance persistence.

1.4.2.1 The Effects of Past Fund Alpha and Information Intensity on Subsequent Fund Performance

We first use the sorted fund portfolio approach to confirm the well-known phenomenon of performance persistence and to examine the relation between information intensity and fund performance. Specifically, in each month, we sort funds into quintiles based on either the past fund alpha or information intensity II. We then form equally weighted fund portfolios within the quintiles and look at the next-month performance of each quintile. Past fund alpha is estimated using the Carhart (1997) four-factor model over the past 12 months up to the end of the ranking month. When we rank funds by II in each month, we use the II estimate based on the rolling four-quarter average of quarterly information intensity (QII) up to the most recent quarter. We report the four-factor alpha of the fund portfolios in Table 1.4. The fund returns used in compute past fund alphas and the subsequent alphas of fund quintile portfolios are both net of fund expenses.

Panel A of the table shows the persistence of performance. Funds in the top past-alpha quintile significantly outperform those in the bottom quintile by 0.272% in terms of monthly four-factor alphas. By contrast, Panel B of the table shows that fund information intensity does not significantly predict fund performance. The difference in fund alphas between the top and bottom II quintiles is 0.079%, positive but statistically insignificant.

The table also reports the dispersion of fund returns within each fund quintile. The dispersion is measured by the cross-sectional standard deviation of monthly fund net returns for a given month, and then averaged over time. The return dispersion is 2.41% for the top II quintile and 1.96% for the bottom quintile, visibly higher than those of the three middle quintiles. Likewise, funds ranked in the top and bottom quintiles of past alphas exhibit high return dispersion.

The insignificant relation between II and subsequent fund performance, and the large performance dispersion among the top II funds, lead us to the conjecture that although information-intense stocks attract many active funds, not all such funds can successfully produce information. An analogy is the great American Gold Rush of the mid-1880s – many aspiring gold seekers went to California, but only a few made a fortune. Their different fortunes are perhaps due in part to luck, and in part to skills. We are more interested in the extent to which skills matter for private-information production in the stock market. This motivates our subsequent analysis.

1.4.2.2 Performance of Fund Portfolios Double-sorted by Information Intensity and Past Alpha

We now turn to a double-sorting approach to see if skill matters for successful information production. In each month, we sort funds independently by past four-factor alpha and information intensity (II) into 5 by 5 (25) groups. Fund alpha is estimated using rolling 12 months returns, and II is the four-quarter rolling average of information intensity up to the most recent quarter. Within each fund group, we form an equal-weighted portfolio and examine its next-month performance. To ensure the robustness of inference, we report post-ranking performance of the 25 portfolios using three performance measures – fund net returns, the four-factor alpha, and the characteristic selectivity measure (CS) of Daniel, Grinblatt, Titman, and Wermers (1997). Specifically, CS is the weighted average of stock return during a month in excess of the corresponding benchmark portfolio return, across all stocks held by a fund. The benchmark portfolios are formed quarterly, based on sequential quintile sorts on market capitalization, book-to-market ratio, and the return during the past 12 months. Stocks in the benchmark portfolios are value-weighted. Note that the net returns and alphas are net of fund expenses, while the DGTW stock selectivity measure is before-expense.

Panels A, B, and C of Table 1.5 report the performance of the double-sorted fund portfolios under these three performance measures respectively. Since the patterns are similar across panels, we focus the discussion on the four-factor alpha (Panel B). Note that the last row of each panel reports the performance difference between the funds in the top and bottom past-alpha quintiles, across funds in different II quintiles. These numbers indicate the magnitude of performance persistence. For funds in the low II quintile, the monthly alpha difference between the top and bottom past-alpha quintile is 0.040%, statistically insignificant. Therefore, there is no performance persistence among low II funds. As we move to funds with higher IIs, performance persistence becomes more visible. Among funds in the top II quintile, those in the top past-alpha quintile outperform those in the bottom past-alpha quintile by 0.448% monthly, or 5.376% annually, with a large t-statistic. Thus, performance is strongly persistent among the top II funds.

The funds in the top past-alpha quintile and in the top II rank worth particular attention. These funds deliver a significantly positive alpha of 0.198% per month, or 2.376% annually. These funds invest in information-intense stocks, and they are skillful in producing information on such stocks. In contrast, the alpha of funds with the same top past-alpha rank but in the bottom II rank is -0.115%, underperforming the afore-mentioned fund group by 0.313% per month. Although these funds have good past performance, their past performance is not the result of intense information production efforts, and thus smacks of random chance that does not last long.

Among funds in the bottom past alpha quintile, those ranked in the top II quintile generate a significantly negative alpha of -0.250%, and those in the bottom II quintile generate a significantly negative alpha of -0.155%. The performance difference between these two groups, at -0.095%, is statistically insignificant. The former group has low information intensity, and thus their poor past performance is more likely due to random chance, while the latter group has high information intensity, and thus their low past performance may be more likely attributable to their ineffectiveness in information production. It is also plausible that these funds are attracted to high II stocks for reasons not related to information production. As noted in the introduction of the paper, high-SII stocks tend to have positively skewed returns, and thus may attract investors with lottery preferences.

To give a quick summary, II has a significant impact on the performance among funds with good past performance, and insignificant impact on the performance of funds with poor past performance. Further, performance persistence mainly exists among funds with high II, and non-existent among low-II funds. These results are consistent with the notion that when funds engage in costly information production and focus their efforts on information-intense stocks, their skills matter for performance; but when funds do not substantially engage in costly information production, their performance has more of a random element and thus lacks persistence.

1.4.2.3 Performance of Fund Portfolios Double-sorted by Information Intensity and Alternative Fund Skills Proxies

In addition to using past fund alpha as a proxy for fund skills, we consider two alternative skill proxies. One is the performance measure based on similarity of fund holdings proposed by Cohen, Coval, and Pastor (2006), and another is the return gap of Kacperczyk, Sialm, and Zheng (2008). The measure ("Similarity" hereafter) of Cohen et al. (2006) is based on the idea that due to scarcity of good investment ideas, skilled fund managers tend to hold similar stocks. Following their study, we construct this measure in two steps. First, we compute a stock quality measure, which is the weighted average of the alphas holding the funds, with weights proportional to the portfolio weight a fund has on the stock. The fund alpha used in this step is the Carhart (1997) four-factor alpha estimated with rolling 12 months of returns. Then, in the second step, the Similarity measure of a fund is the weighted average of the stock quality measure across stock holdings of the fund, with weights being the portfolio weights. The return gap ("Return Gap" hereafter) is the difference between the reported fund return and the hypothetical return inferred from the beginning-of-period fund holdings. It follows the idea that unobserved actions by mutual funds (relative to the prior-disclosed portfolio holdings) matter for fund performance. Conceptually, this measure captures the interim trading skills of mutual funds, rather than the conventional notion of stock selection (i.e., picking stocks at the beginning of a period and holding them throughout the period). However, in analyzing the relation between GAP and subsequent fund performance, Kacperczyk, Sialm, and Zheng (2008) show that GAP is significantly related to the subsequent characteristic selectivity of Daniel, Grinblatt, Titman, and Wermers (1997).

Thus, the interim trading skills are at least correlated with the stock selection ability of fund managers.

Table 1.6 reports the performance of fund groups double-sorted by II and one of the two alternative skill proxies. Again, we perform independent double-sorts monthly to form 25 (5 by 5) equal-weighted fund portfolios and examine their next-month performance. The performance measure reported in the table is the after-expense four-factor alpha. The patterns observed here are quite similar to those in Table 1.5. The subsequent performance difference between the top and bottom Similarity quintiles is significant only among funds in the top two II quintiles. And the subsequent performance difference between the top and bottom Return Gap quintiles is significant only among the funds in the top II quintiles. Further, despite being statistically significant, the results based on Return gap are overall weaker relative to those based on past four-factor alphas or Similarity. This is perhaps due to that GAP is related to both interim trading skills and stock selection skills, and more to the former.

1.4.2.4 The Effect of Lagged Information Intensity Measures

Fund information intensity measure II depends on fund holdings data, and information about fund holdings is typically available with delays. In this part, we examine whether delayed measures of fund information intensity is still useful to fund investors when they make fund selection decisions.

There are at least two types of delays that are relevant here. The first is due to reporting lag of fund holdings – mutual funds have at most 60 days after the end of their fiscal quarter to disclose their holdings via SEC's EDGAR system. The second is that data vendors such as Thomson-Reuters may include the newly disclosed holdings into their datasets with a time lag.[12] By contrast, fund returns are reported in a more timely manner. Due to the requirement of daily pricing of fund net asset values (NAV), fund return is available at the daily frequency and by the end of a day.

Note that as described in Equations (8), (8), and (10), the latest fund holdings used to compute fund II for a given calendar quarter are those at the end of the previous calendar quarter. Thus, the results reported in Table 1.5 are based on fund holdings information already disclosed by funds at the time of fund ranking, and thus are not subject to the first type of delays described above. However, they may still be subject to the second type of delays on the part of data vendors. To address this concern, we use lagged fund IIs to repeat the double-sorting analysis performed in Table 1.5.

Panels A of Table 1.7 reports the performance of double-sorted fund portfolios where fund IIs are lagged by one quarter relative to the II measures used in Table 1.5. To give a concrete example, when we double-sort funds in July of a given year, past fund alphas are still estimated for the 12 months up to the end of July (assuming no reporting delays for fund returns), but fund IIs are estimated in March of that year, which involves fund holdings in the fourth calendar quarter of the previous year. The performance measure reported in the table is the after-expense four-factor fund alpha. The results show that among funds ranked in the top lagged-II quintile, the alpha difference between the top and bottom fund quintiles sorted on past alpha is 0.445%, comparable to the corresponding number reported in Table 1.5 (0.448%). The funds ranked in the top past-alpha quintile and top II quintile

[12] A small number of funds report their holdings to data vendors via direct data feeds shortly after their fiscal quarter-end or even at the monthly frequency. Thus, their holdings information may become available in the datasets before funds file their holdings disclosure via EDGAR. However, this is not the case for the majority of funds.

have an alpha of 0.201%, also comparable to the corresponding number reported in Table 1.5 (0.198%). Thus, lagging fund IIs by one quarter does not significantly reduce the effect of fund II on performance persistence.

In Panels B to D of Table 1.7, we lag fund IIs by two to four quarters. The results show that when we take longer lags on II, its effect on performance persistence tends to become weaker. However, even after lagging fund IIs by four quarters, the effect of II on performance persistence remains significant. What we observe from this table is to a large extent consistent with the persistence of fund II reported in Table 1.3. These findings highlight the practical usefulness of the fund information intensity measure to fund investors when they make fund selection decisions.

1.4.2.5 Subperiod Analysis

Barras, Scaillet, and Wermers (2010) and Fama and French (2010) document that the proportion of truly skilled active funds in the market shrinks substantially over time. One possible reason for such a time trend is improved market efficiency. In theory, if market efficiency in both the semi-strong form and the strong form improves over time, any type of fundamental research, whether it is based on public information or private information, should exhibit reduced profitability. However, we note that there are countervailing factors in the market, which may keep the opportunities alive for private information production. One particular factor is the tightening regulations (e.g., Reg FD) on corporate disclosure and insider trading, which, for the purpose of fairness and investor protection, may have an effect of delaying the release of private information to the public. Such a slow-down of releasing private information creates profit opportunities for investors who can uncover information on their own means.[13] Therefore, it is interesting to see the time trend in the effectiveness of private information production by fund managers.

In Table 1.8, we break the entire sample period of 1980-2014 into two subperiods, 1980-1996 and 1997-2014, and repeat the double-sort analysis of Table 1.5 for each of the subperiod. The performance measure reported in the table is the after-expense four-factor fund alpha. The results show that during the early subperiod, the relation between II and performance persistence is very strong. Among the funds in the top II quintile, the alpha difference between the top and bottom past-alpha quintiles is 0.532%. During the later subperiod, the alpha difference between the top and bottom past-alpha quintiles is lower, at 0.352%; however, such a performance difference remains statistically significant. Thus, improved market efficiency weakens, but does not completely wipe out the effectiveness of fund managers' private information production efforts during the more recent years. In other words, the more recent version of fundamental research remains useful as a stock selection approach.

1.4.3 Comparison with and Controlling for Alternative Effects

In this part of the analysis, we compare the effect of information intensity on fund performance with several competing effects. In Section 1.4.3.1, we document the effect of the fund holdings' volatility and the effect of fund return R-square (R2) on fund performance. In Section 1.4.3.2, we control for various competing effects using a triple-sorting procedure. In Section **??**, we use multivariate regressions to examine the effect of information

[13] Regulations may also affect the specific methods of uncovering private information. For example, some practices once popular among investors to uncover private information –e.g., expert network – have been essentially outlawed, while others –e.g., channel-checking – remain legitimate or in the grey area.

intensity on fund performance while controlling for various competing effects.

1.4.3.1 Fund Holdings Volatility and R2

The stock-level information intensity is based on a decomposition of return volatility – the return variance attributed to large price jumps relative to the total variance. It is natural to question how important it is to separate the jump component from the diffusion component in defining information intensity. Note that at the stock level, there is a well-known low volatility anomaly – stocks with high return volatility (idiosyncratic or total volatility) tend to have abnormally low subsequent returns (Ang, Hodrick, Xing, and Zhang, 2006). At the fund level, a recent study by Jordan and Riley (2015) reports a related phenomenon – funds with high return volatility tend to have poor subsequent performance. They attribute this fund level relation to the volatility of stocks held by funds. Finally, our Table 1.2 shows that funds with high II also tend to hold stocks with high realized variance (RV) and high return standard deviation. Given all these considerations, it is important to understand the relation between the information intensity effect and the effect of return volatility of stocks held by funds.

To quantify this volatility effect, we use the variable reported in Table 1.2 – STDEV, which is the weighted average return standard deviation of stocks held by the fund. The weights are the portfolio weights at the beginning of a holding quarter. The return standard deviation of a stock is computed using daily returns during the quarter. Similar to the construction of fund II, we take the rolling 4-quarter averages of the quarterly weighted average return standard deviation to obtain STDEV. Then, in each month, we form 25 (5 by 5) equal-weighted fund portfolios independently double-sorted on past 12-month four-factor alpha and STDEV.

Panel A of Table 1.9 reports the performance of the 25 fund portfolios. Again, we focus on the four-factor alphas during the subsequent month. The results show that STDEV also has a significant impact on fund performance persistence. Specifically, performance persistence, as measured by the performance difference between funds in the top and bottom past-alpha quintiles, is stronger among funds with higher STDEV. Interestingly, a closer look at the results reveals that the volatility effect is different from that of information intensity. Recall that in Table 1.5 and discussed earlier, II affects performance persistence mainly through predicting the performance of funds with high past alphas. In contrast, the volatility effect here works mainly through its impact on the performance of funds with low past alphas. For example, among funds with the bottom past alpha rank, those with the top STDEV rank generate a significantly negative four-factor alpha of -0.390%. They significantly underperform those with the bottom STDEV rank, which have an insignificantly negative alpha of -0.072%. Meanwhile, among funds with the top past alpha rank, the relation between STDEV and performance is basically flat – those in the top STDEV rank generate a four-factor alpha of 0.062%, indifferent from the alpha generated by those with the bottom STDEV rank (0.016%).

This comparison suggests that the effects of stock holdings volatility and information intensity are different. The information intensity measure II captures the effect associated with costly information production, while the volatility effect likely represents a different phenomenon – for example, as discussed in the introduction of the paper, investors' preference for lottery-like stocks. It is worthwhile noting that we have also performed analysis using two other measures of volatility – the weighted RV and the weighted BPV of stocks held by funds. The effects of these two measures on fund performance persistence are similar to that of STDEV. This is perhaps largely due to the high correlation among RV, BPV, and STDEV at the fund level and at the stock level.

Next, we turn to another fund characteristic known to affect fund performance and performance persistence. Amihud and Goyenko (2013) report that their fund activeness measure R2 has a significantly negative relation with subsequent fund performance, and that its effect is particularly strong among funds with high past alphas. Panel B of Table 1.9 by and large confirms their results. Here, funds are independently double-sorted by past alpha and R2. As noted in Section 1.4.1, we follow Amihud and Goyenko (2013) to estimate fund R2 as the R-square obtained from the Carhart four-factor regression model based on past 24 months of fund returns. The results from the last row of the panel show that the performance difference between the top and bottom past-alpha fund quintiles, a measure of performance persistence, decreases with R2 quintile ranks. The top-bottom performance difference is 0.386% for the bottom R2 quintile, and 0.138% for the top R2 quintile. In addition, the last column of the panel shows that R2 does not significantly affect fund performance among funds in the lowest past-alpha quintile, but significantly affects fund performance among funds in the top past-alpha quintile. These observed effects of R2 on fund performance are similar, although at a weaker magnitude, to those reported for information intensity in Table 1.5.

The results reported in Panel B are also somewhat weaker relative to those reported by Amihud and Goyenko (2013). We conjecture that the difference is caused by further nuances in sample construction. In Panel C of Table 1.9, we repeat the analysis of Panel B by adopting two additional sample restrictions of Amihud and Goyenko (2013): 1) censoring

R2 at the top and bottom 1% each month, and 2) restricting the sample period to 1990-2010. The results are stronger.

Since the results here suggest that the effect of R2 is somewhat similar to that of II, it would be interesting to further disentangle these two effects. We do so in subsequent analysis. In addition to R2, we have performed similar double-sorting analysis involving another fund activeness measure, ActiveShare. We find that ActiveShare does not have a significant impact on fund performance persistence.

1.4.3.2 Controlling for Competing Effects Using Triple-sorted Fund Portfolios

In this part of the analysis, we use the triple-sorted portfolio approach to examine the effect of information intensity on performance persistence while controlling for various competing effects. The triple-sorting procedure works as follows. First, we sort funds into quintile by a fund characteristic representing a competing effect that is to be controlled. Then, within each quintile of the first sorting variable, we further use independent double sorts to rank funds into II quintiles and past four-factor alpha quintiles. This results into 125 fund groups. Finally, we combine funds with the same quintile ranks on II and past alpha but different quintile ranks of the first sorting variable into a single equal-weighted portfolio. This procedure results in 25 (5 by 5) fund portfolios, and within each portfolio, fund characteristic represented by the first sorting variable is distributed relatively evenly across fund portfolios. Thus, if we continue to observe significant impact of II on performance persistence across the 25 portfolios, then such an effect of II cannot be attributed to the competing effect represented by the first sorting variable. Note that similar procedures to control for competing effects have been used in previous studies, e.g., Ang, hodrick, Xing, and Zhang

(2006).

We control for three sets of competing effects. The first set is related to market frictions. As pointed out in the introduction part of the paper, information intensity is conceptually different from mispricing, with the former pertaining more to private information and the latter relative to public information. However, information intensity may have an intertwined relation with market frictions such as illiquidity, which may exacerbate mispricing. In particular, investors tend to pay low attention to small stocks and illiquid stocks, and as a consequence these stocks may surprise investors from time to time by significant news. However, stocks could also generate large surprises for reasons unrelated to market frictions – for example, to avoid competition, a firm may provide little voluntary disclosure but instead release a large amount of information at the time of mandatory disclosure (e.g., earnings announcements). Therefore, we expect the effect of market frictions on fund performance to be related to, but do not subsume the effect of information intensity. We use two fund characteristics reported in Table 1.2 – SIZESCORE and ILLIQSCORE – to quantify the effect of market frictions a fund faces.

The second set of effects to control for is fund activeness, and we include two fund activeness measures – ActiveShare and R2. The last set of competing effect is the return volatility of fund stock holdings, and the variable to control for is the weighted average return standard deviation of stocks held by a fund, STDEV.

Panels A to E in Table 1.10 report the results of the triple-sorting analyses that control for the above-mentioned effects. The results show that the significant effect of II on performance persistence is not explained away by any of the competing effects.[14]

1.4.3.3 Multivariate Regressions

We further perform Fama-MacBeth multivariate regressions to analyze the impact of information intensity on fund performance while controlling for various fund characteristics affecting fund performance. The regressions are performed each month t across sample funds. The dependent variable is fund abnormal return during month t under the Carhart four-factor model (referred to as the "four-factor abnormal return"). Specifically, a fund j's four-factor abnormal return $\hat{\alpha}_{j,t}$ is estimated as:

$$\hat{\alpha}_{j,t} = r_{j,t} - r_{ft} - (\hat{\beta}_{j,1,t-1}\text{MKTRF}_t + \hat{\beta}_{j,2,t-1}\text{SMB}_t + \hat{\beta}_{j,3,t-1}\text{HML}_t + \hat{\beta}_{j,4,t-1}\text{UMD}_t) \quad (11)$$

where $r_{j,t}$ is fund j's month-t after-expense net return, r_{ft} is the riskfree rate, and MKTRF, SMB, HML, and UMD are the market, size, book-to-market, and momentum factors. $\hat{\beta}_{j,1,t-1}$, $\hat{\beta}_{j,2,t-1}$, $\hat{\beta}_{j,3,t-1}$, and $\hat{\beta}_{j,4,t-1}$ are the estimated fund loadings to the four factors. These loadings are estimated using past 36 months of data (month t-36 to month t-1) under the Carhart four-factor model. We require a fund to have a minimum of 24 months of data for the factor loading estimates (and consequently, for the abnormal return estimates) to be valid.

The main explanatory variables include past fund alpha, the information intensity measure II, and the interaction between past alpha and II. Past alpha is estimated from the Carhart four factor model using rolling 12 months of returns, i.e., month t-12 to month

[14]Again, since our data for ActiveShare is for the period of 1981-2012, the results in Panel C are based on that sample period.

t-1. In addition, we control for a set of common fund characteristics, including the natural log of fund TNA, annual expense ratio, log fund age, turnover, and percentage fund flow. These variables are measured as of end of month t-1. In addition, to control for the effect of market frictions and the effect of fund activeness, we include SIZESCORE, ILLIQSCORE, and ActiveShare, and their interaction terms with past fund alpha as additional explanatory variables. Again, these variables are constructed using data available at the end of month t-1. Also, as noted earlier, since our ActiveShare data are for the period of 1981-2012, the regressions involving this variable are for that particular sample period. To facilitate interpretation of the regression results, we cross-sectionally standardize key variables involved in the interaction terms (i.e., subtracting their cross-sectional means and then dividing them by the cross-sectional standard deviations); these standardized variables include past alpha, II, SIZESCORE, ILLIQSCORE, and ActiveShare.

The regression results are reported in Panel A of Table 1.11. The first regression, reported in Column (1), controls for a set of common fund characteristics but does not control for the effect of market frictions or fund activeness. The coefficient for the key variable of interest, the interaction term II*Past Alpha, is 0.0279, significantly positive. This suggests that information intensity has a significant impact on the relation between past performance and subsequent performance. In addition, the coefficient on II per se is insignificant. Note that the interaction term II*Past Alpha is close to zero for a typical fund whose alpha is close to zero. Thus, the insignificant coefficient on II means that for an average fund, II has no impact on subsequent performance, consistent with the results from the single-sort analysis reported in Table 1.4. Finally, the coefficient on past alpha per se is also insignificant. This suggests that information intensity soaks up all the performance persistence effect.

Regressions reported in Columns (2) to (4) control for the effects of SIZESCORE, ILLIQSCORE, and ActiveShare, respectively. Three of the four variables – SIZESCORE, ILLIQSCORE, and ActiveShare, do not have significant coefficients; nor are the coefficients on their interaction terms with past alpha. This suggests that fund investments in small and illuiqid stocks and fund ActiveShare do not directly impact performance or performance persistence.[15]

As shown in Table 1.9, return volatility of fund holdings STDEV and the fund activeness measure R2 have significant impact on performance persistence; further, they have quite different effects on the performance of funds with low and high past alphas. To properly control for their differential impact on fund performance, we perform a separate set of regressions in Panel B of Table 1.11. In this panel, we create five dummies for funds ranked in the five past-alpha quintiles, referred to as "past $\alpha 1$" to "past $\alpha 5$". We further create three sets of interaction terms involving the past-alpha dummies. These dummy variables are interacted with 1) the information intensity measure II, 2) the logistic transformation of R2 ("TR", following Amihud and Goyenko, 2013), and 3) the measure of fund holdings' return volatility, STDEV. Other control variables are similar those in Panel A of the same table. Again, key variables involved in the interaction terms, including past alpha, II, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

The results in this panel show that the interaction between the top past-alpha dummy and II remains significant in all regression specifications, suggesting that the effect of informa-

[15] Note that the dependent variable of the regressions is already the four-factor abnormal return. This might explain the insignificant coefficient of SIZESCORE. In addition, Cremers and Petajisto (2009) report that ActiveShare does not significantly predict the four-factor alpha of funds (their Table 1.8) but significantly predicts the benchmark-adjusted fund performance (their Table 1.4). The dependent variable of our regressions is the four-factor alpha. Thus the insignificant coefficient on ActiveShare we obtain here is consistent with their findings.

tion intensity in predicting fund performance among high past alpha funds is not explained away by the effects of R2 or volatility, or other fund characteristics controlled for. The interaction term between the bottom alpha dummy and STDEV is significantly negative while the interaction between the top alpha dummy and STDEV is insignificant, consistent with the notion that volatility of fund holdings mainly predicts performance among the low alpha funds. The interaction term between the top alpha dummy with R2, however, does not consistently produce significant coefficients across various regression specifications.

We have performed additional regressions to ensure the robustness of inference. For brevity we discuss them here without tabulating the results. First, we perform regressions involving the logit transformed R2 (TR) for the subperiod studied by Amihud and Goyenko (2013) and with R2 censored at the top and bottom 1%. The coefficient for the interaction term between II and top alpha dummy remains significant, suggesting that during this subperiod the effect of II is not subsumed by that of R2. Second, we also control for an effect known as “reliance on public information”. This effect is documented by Kacperczyk ad Seru (2007). They quantify funds’ reliance on public information based on how closely fund portfolio weight changes tracks analyst recommendation changes. We follow their study to construct the measure RPI and perform regression analysis for the subperiod of time of 1994-2015 when analyst recommendation data necessary for constructing RPI are available. The results show that the effect of II is not subsumed by RPI.

1.4.4 Fund Performance around Corporate Events

In this section, we take a closer look at the specific types of information fund managers may uncover from high II stocks. Previous studies have shown that a variety of corporate events and news cause large price movements.[16] Unfortunately, tracking all the wide varieties of events is impossible. Instead, we focus on two types of corporate events – earnings announcements and M&A announcements. To gauge the impact of the events to stock returns, we compute the event window return as the cumulative stock return during the five-day window, from two days before the announcement date to two days after. We then compute the quarterly fund-level event-window performance as the weighted average event-window returns during a quarter for stocks held by the fund, using the beginning-of-quarter portfolio weights. Given the association between these two types of events and stock price jumps, the event-window performance at least in part reflects the effectiveness of funds in turning rewarding information production opportunities into actual information production.

Table 1.12 reports the event-window performance of funds double-sorted by past alpha and II. Panel A is for the event-window performance during the 4 quarters prior to fund ranking. Funds ranked in the bottom quintile of past alpha, regardless of their II rank, ramp up significant losses during the event windows. Among these funds, the event-window performance difference between the top and bottom II quintiles is insignificant. By contrast, funds ranked in the top past alpha quintile experience significant profits during the event windows. Among these funds, there is a significant difference in event-window performance between the top and bottom II quintiles. It seems that the event-window performance is an important

[16]For example, Jiang and Yao (2013) report that during the period from 1974 to 2009, about 10% of jumps take place during earnings announcement windows, and about 12% of earnings announcements trigger jumps. In an unpublished appendix, they identify all events associated with price jumps for stocks in the Dow Jones Industrial Average during the two year period from July 2003 to June 2005. These events include earnings announcements, management earnings forecasts, macroeconomic news, legal events, analyst forecast and recommendation changes, mergers and acquisitions, significant product failures, management turnover, news about sales, news about industry peers, stock repurchases, dividends, spinoffs, and union negotiations.

source of performance difference during the fund ranking period.

Panel B of the table reports the event-window performance during the quarter after fund ranking. Across funds ranked in the bottom quintile of past alpha, the event-window performance tends to be insignificant and there is no significant difference between the top and bottom II quintiles. In contrast, among funds ranked in the top past alpha quintile, the event-driven performance is significantly positive for the top-II quintile, and there is a significant difference in event-window performance between the top and bottom II quintiles. Finally, in top II quintile, there is a significant event-window performance difference between the top and bottom past alpha quintiles, while the difference is insignificant within the bottom II quintile. These patterns are consistent with those based on the overall fund performance reported in Table 1.5, thus offering support to the notion that skills in information production make a big difference when investing in high information intensity stocks.

Between the two types of events, earnings announcements occur much more frequently and M&A announcements are sporadic. We have also estimated the event-window performance using the single type of event of earnings announcements. The results are largely similar.

1.4.5 Information Intensity and Fund Flow Sensitivity to Past Performance

Given the significant impact of information intensity in predicting fund performance, we ask whether fund investors are aware of this impact and allocate their fund investments accordingly. We examine fund investors' decisions via fund flows, and use Fama-MacBeth regressions to see how information intensity affects fund flow response to past performance. The dependent variable of the regressions is the percentage fund flow during the quarter after fund ranking.[17] The main explanatory variables of interest include past fund alpha (the four-factor alpha using rolling 12-month estimation), II, and the interaction term between past alpha and II. The common control variables are similar to those in Table 1.11 – the natural log of fund TNA, annual expense ratio, log fund age, turnover, and lagged fund flow. In addition, we include SIZESCORE, ILLIQSCORE, ActiveShare, and their interaction terms with past fund alpha as additional explanatory variables. Again, because volatility and R2 exhibit differential effect on fund performance across past alpha groups, we create a separate set of regressions involving past alpha quintile dummies and their interactions with STDEV and TR, the logistic transformation of R2. Similar to Table 1.11, key variables involved in the interaction terms, including past alpha, II, SIZESCORE, ILLIQSCORE, ActiveShare, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

Panel A and B of Table 1.13 report the results. Across various regression settings, the coefficient for the main variable of interest, the interactions between II and past alpha in Panel A and the interactions between the top alpha dummy with II in Panel B, tend to be significantly positive. The results suggest that fund flows are extra sensitive to past performance when fund information intensity is high. Therefore, to a large extent, fund investors are aware of the role of information intensity in generating performance persistence, and guide their fund investment decisions accordingly. A qualification to this inference is that in the regression specification (4) and (5) reported in Panel A, when we control for the effects of SIZESCORE and ILLIQSCORE jointly, or additionally jointly control for the effect of ActiveShare, the coefficient for the interaction between II and past alpha becomes

[17] We use quarterly fund flows instead of monthly flows, because in early sample years fund TNAs are available only at the quarterly frequency.

insignificant.

1.5 Conclusions

We propose a measure on the information intensity of mutual fund investment strategies and examine the impact of information intensity on fund performance. Stocks with high information intensity attract active fund managers. On average, funds investing mostly in high information intensity stocks do not generate superior performance. But within these funds, skills in information production matter for performance. Skilled funds such as those with high past alphas are able to successfully generate information and deliver outperformance, while unskilled funds experience poor performance despite their investment in information-intense stocks. In contrast, there is no performance persistence among funds that invest mostly in low information intensity stocks. Further analysis shows that the effect of fund information intensity on performance persistence is different from the effect of the return volatility or illiquidity of fund stock holdings, and different from the effect of existing measures of fund activeness. Finally, information intensity increases fund flow sensitivity to past performance. These findings suggest that in the presence of significant information production cost, information intensity is an important dimension of the active investment decisions by fund managers and the fund selection decisions by investors.

Table 1.1: Summary Statistics

This table provides summary statistics on the sample of mutual funds and their stock holdings each year from 1980 to 2014. We report the number of funds, the average number of stocks held per fund, the average total net assets, the average annual expense ratio, the average fund turnover ratio, the average and cross-sectional standard deviation of fund information intensity II.

Year	Number of Funds	Number of Holdings	TNA ($m)	Expense (%)	Turnover (%)	Average II (%)	Stdev of II (%)
1980	216	57	192	0.96	70	8.28	2.41
1981	228	60	177	0.96	67	8.70	2.61
1982	229	57	217	0.97	73	8.93	2.67
1983	253	66	272	0.97	74	8.68	2.56
1984	282	66	264	0.98	72	9.55	2.35
1985	310	66	336	0.99	77	8.41	1.91
1986	349	69	374	1.02	79	8.39	1.63
1987	403	71	354	1.11	93	8.61	1.40
1988	421	72	373	1.22	83	9.56	1.30
1989	468	74	438	1.28	83	9.55	1.47
1990	494	72	402	1.29	88	7.19	1.81
1991	578	78	529	1.24	89	7.83	1.43
1992	651	79	610	1.26	82	7.40	1.56
1993	805	86	684	1.25	83	7.93	1.37
1994	957	92	657	1.24	82	8.05	1.51
1995	1,083	94	861	1.25	88	8.25	1.55
1996	1,172	99	1,051	1.26	88	8.86	1.52
1997	1,344	98	1,249	1.25	89	8.04	1.91
1998	1,462	95	1,391	1.27	91	7.57	2.09
1999	1,593	96	1,633	1.29	100	7.49	2.36
2000	1,789	100	1,471	1.30	107	7.63	1.65
2001	1,885	103	1,238	1.34	103	8.17	1.46
2002	1,964	103	947	1.37	99	7.49	1.48
2003	1,983	109	1,244	1.40	89	9.51	1.81
2004	2,063	110	1,387	1.35	83	9.91	1.97
2005	2,092	110	1,507	1.30	85	10.96	2.48
2006	2,049	113	1,728	1.28	86	12.22	1.93
2007	2,173	122	1,778	1.22	94	10.82	1.89
2008	2,148	125	1,038	1.21	107	8.44	1.44
2009	2,155	134	1,349	1.23	93	8.85	1.36
2010	2,012	133	1,539	1.20	84	11.23	1.50
2011	1,928	126	1,522	1.17	79	9.14	1.56
2012	1,793	128	1,728	1.15	73	11.91	2.01
2013	1,673	128	2,344	1.12	66	11.69	2.00
2014	1,594	129	2,505	1.09	64	10.97	2.10

Table 1.2: Characteristics of Funds across Information Intensity Quintiles

This table reports the average fund characteristics across information intensity quintiles. In each quarter, we sort funds into quintile portfolios based on information intensity (II). Panel A reports the following fund characteristics: II, the weighted averages of JV, RV, return standard deviation (STDEV), two measures of fund activeness ActiveShare and R2, the number of stock holdings, and annual fund turnover. Panel B reports the following fund characteristics: fund TNA, expense ratio, age, and four scores that measure fund styles along the dimensions of market cap, book-to-market ratio, momentum, and illiquidity — SIZESCORE, BMSCORE, MOMSCORE, and ILLIQSCORE.

Panel A: Fund Activeness

II Rank	II (%)	JV (%)	RV (%)	STDEV (%)	ActiveShare	R2	# Holdings	Turnover (%)
1-Low	6.87	0.43	5.23	1.96	0.77	0.92	75	77
2	7.93	0.53	5.35	2.01	0.78	0.93	98	80
3	8.74	0.66	5.93	2.13	0.83	0.92	102	84
4	9.78	0.92	7.21	2.34	0.89	0.91	102	90
5-High	11.77	1.37	8.85	2.60	0.94	0.90	99	89
High-Low	4.90	0.94	3.62	0.63	0.17	-0.02	25	13
t stat	(22.51)	(9.16)	(8.02)	(9.17)	(13.33)	(-3.18)	(9.44)	(3.34)

Panel B: Fund Characteristics

II Rank	TNA ($m)	Fee (%)	Age (Yrs)	SIZESCORE	BMSCORE	MOMSCORE	ILLIQSCORE
1-Low	1,417	1.11	19.9	4.67	-5.288	0.176	-0.127
2	1,323	1.11	18.9	4.09	-5.378	0.165	-0.126
3	1,056	1.17	17.0	3.00	-5.269	0.176	-0.125
4	778	1.24	14.9	1.74	-5.317	0.213	-0.122
5-High	526	1.32	12.5	0.67	-5.537	0.229	-0.117
High-Low	-892	0.21	-7.4	-3.99	-0.249	0.053	0.010
t stat	(-4.96)	(13.29)	(-6.19)	(-13.88)	(-1.27)	(1.68)	(2.34)

Table 1.3: Persistence of Information Intensity

This table reports the persistence of fund information intensity II. In each quarter, we sort funds into quintile portfolios based on II, and calculate the average II for quintile portfolios during each of the subsequent five years. II is expressed in percentage points.

II rank	Year 1	Year 2	Year 3	Year 4	Year 5
1-Low	7.71	8.16	8.34	8.47	8.58
2	8.47	8.65	8.78	8.85	8.91
3	9.18	9.22	9.26	9.28	9.31
4	10.10	10.06	10.05	10.02	10.02
5-High	11.61	11.27	11.13	11.09	11.08

Table 1.4: Performance of Fund Portfolios Sorted by Past Alpha and by Information Intensity

This table reports the performance of sorted fund portfolios. In each month, we sort funds into equal-weighted quintile portfolios based on either past 12-month four-factor alpha (Panel A) or Information Intensity II (Panel B). We report the after-expense four-factor alpha of each portfolio, and the average standard deviation of the net returns across funds in each portfolio. The four-factor alpha and standard deviation are both reported in percentage points.

Panel A: Funds Sorted by Past Alpha

	1-Low	2	3	4	5-High	High-Low
Alpha (%)	-0.216***	-0.109***	-0.079***	-0.067**	0.056	0.272***
t stat	(-4.41)	(-3.29)	(-2.75)	(-2.23)	(1.17)	(4.21)
Return Dispersion (%)	2.45	1.97	1.91	2.01	2.51	0.06

Panel B: Funds Sorted by Information Intensity

	1-Low	2	3	4	5-High	High-Low
Alpha (%)	-0.118***	-0.110***	-0.086***	-0.064	-0.039	0.079
t stat	(-3.37)	(-4.15)	(-2.64)	(-1.59)	(-0.74)	(1.28)
Return Dispersion (%)	1.96	1.84	2.07	2.29	2.41	0.46

Table 1.5: Performance of Fund Portfolios Double-Sorted by Past Alpha and Information Intensity

This table reports performance of fund portfolios formed on monthly independent double-sorts by past alpha and information intensity II. Past alpha are estimated from the Carhart four-factor model using rolling 12-month after-expense fund returns. The performance measures include after-expense net return (Panel A), after-expense four factor alpha (Panel B), and the Characteristic Selectivity (Panel C), all reported in percentage points.

Panel A: Net Return

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	0.805***	0.829***	0.808***	0.788***	0.830***	0.025
	(3.72)	(3.80)	(3.61)	(3.28)	(3.25)	(0.23)
2	0.851***	0.854***	0.890***	0.955***	0.927***	0.075
	(4.05)	(4.11)	(4.18)	(4.20)	(3.84)	(0.73)
3	0.865***	0.855***	0.908***	0.995***	1.024***	0.159
	(4.14)	(4.17)	(4.27)	(4.42)	(4.35)	(1.60)
4	0.869***	0.878***	0.932***	0.967***	1.095***	0.226**
	(4.16)	(4.24)	(4.29)	(4.32)	(4.63)	(2.15)
5-High	0.874***	0.946***	1.011***	1.179***	1.248***	0.374***
	(3.78)	(4.16)	(4.38)	(4.74)	(5.00)	(3.30)
High-Low	0.069	0.118	0.202**	0.391***	0.417***	0.348***
	(0.89)	(1.59)	(2.50)	(4.44)	(5.50)	(3.68)

Panel B: Four-factor Alpha

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.155***	-0.143***	-0.161***	-0.243***	-0.250***	-0.095
	(-2.71)	(-3.06)	(-2.84)	(-3.94)	(-3.49)	(-1.09)
2	-0.110***	-0.125***	-0.101**	-0.085*	-0.139**	-0.029
	(-3.09)	(-3.98)	(-2.48)	(-1.72)	(-2.24)	(-0.41)
3	-0.112***	-0.112***	-0.089**	-0.049	-0.031	0.081
	(-3.66)	(-3.77)	(-2.36)	(-1.04)	(-0.53)	(1.26)
4	-0.098***	-0.113***	-0.090**	-0.062	0.032	0.129**
	(-2.63)	(-3.49)	(-2.30)	(-1.32)	(0.60)	(2.06)
5-High	-0.115	-0.071	-0.038	0.119**	0.198***	0.313***
	(-1.62)	(-1.26)	(-0.76)	(2.03)	(3.33)	(3.70)
High-Low	0.040	0.073	0.123*	0.362***	0.448***	0.408***
	(0.51)	(1.06)	(1.65)	(4.38)	(6.01)	(4.23)

Panel C: Characteristic Selectivity

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.075	-0.056	-0.062	-0.082*	-0.039	0.035
	(-1.29)	(-1.16)	(-1.35)	(-1.65)	(-0.74)	(0.50)
2	-0.037	-0.014	-0.004	0.028	0.004	0.041
	(-0.77)	(-0.35)	(-0.10)	(0.68)	(0.08)	(0.65)
3	-0.022	-0.023	-0.007	0.042	0.025	0.047
	(-0.47)	(-0.56)	(-0.17)	(1.14)	(0.63)	(0.80)
4	-0.022	-0.011	0.022	0.017	0.055	0.077
	(-0.48)	(-0.28)	(0.60)	(0.45)	(1.37)	(1.33)
5-High	-0.048	0.019	0.023	0.118***	0.148***	0.196***
	(-0.81)	(0.45)	(0.58)	(2.59)	(3.14)	(2.88)
High-Low	0.027	0.075	0.086*	0.200***	0.187***	0.160**
	(0.44)	(1.52)	(1.70)	(3.88)	(3.85)	(2.40)

Table 1.6: Performance of Fund Portfolios Double-Sorted by Alternative Fund Skill Proxies and Information Intensity

This table reports performance of fund portfolios formed on monthly independent double-sorts by alternative fund skill proxies and information intensity II. The reported performance is the after-expense four factor alpha, in percentage points. The alternative fund skill proxies are Similarity and Return Gap. In Panel A, funds are double-sorted by Similarity and II. In Panel B, fund are double-sorted by Return Gap and II.

Panel A: Funds double-sorted by Similarity and II

	II					
Similarity	1-Low	2	3	4	5-High	High-Low
1-Low	-0.058	-0.126*	-0.091	-0.195**	-0.216**	-0.158
	(-0.75)	(-1.69)	(-1.22)	(-2.45)	(-2.54)	(-1.58)
2	-0.072	-0.128***	-0.068	-0.093	-0.096	-0.024
	(-1.62)	(-3.24)	(-1.37)	(-1.45)	(-1.17)	(-0.28)
3	-0.122***	-0.106***	-0.140***	-0.095*	0.003	0.126
	(-3.28)	(-3.69)	(-3.61)	(-1.70)	(0.04)	(1.35)
4	-0.111*	-0.123**	-0.109**	-0.050	-0.008	0.103
	(-1.76)	(-2.51)	(-2.56)	(-0.99)	(-0.13)	(1.07)
5-High	-0.124	-0.063	-0.015	0.083	0.124**	0.248**
	(-1.21)	(-0.74)	(-0.19)	(1.19)	(1.98)	(2.54)
High-Low	-0.066	0.063	0.077	0.279**	0.340***	0.406***
	(-0.50)	(0.48)	(0.61)	(2.36)	(3.26)	(3.44)

Panel B: Funds double-sorted by Return Gap and II

	II					
Gap	1-Low	2	3	4	5-High	High-Low
1-Low	-0.104*	-0.127***	-0.088*	-0.043	-0.086	0.018
	(-1.89)	(-2.65)	(-1.69)	(-0.78)	(-1.40)	(0.24)
2	-0.106***	-0.074**	-0.064*	-0.083	-0.057	0.049
	(-2.68)	(-2.51)	(-1.66)	(-1.64)	(-0.94)	(0.69)
3	-0.088***	-0.071**	-0.085**	-0.075	-0.013	0.075
	(-2.59)	(-2.25)	(-2.10)	(-1.60)	(-0.20)	(1.07)
4	-0.107***	-0.135***	-0.126***	-0.069	-0.077	0.030
	(-2.85)	(-3.84)	(-2.96)	(-1.40)	(-1.23)	(0.43)
5-High	-0.140**	-0.132***	-0.103**	-0.071	0.036	0.176**
	(-2.30)	(-2.82)	(-2.26)	(-1.34)	(0.59)	(2.16)
High-Low	-0.036	-0.006	-0.015	-0.028	0.122**	0.158**
	(-0.54)	(-0.10)	(-0.24)	(-0.44)	(1.96)	(2.05)

Table 1.7: The Effect of Lagged Information Intensity Measures on Performance Persistence

This table reports the performance of fund portfolios using lagged fund II. Each month, we double-sort funds independently by past 12-month four-factor fund alpha and lagged information intensity measures into 5 by 5 (25) groups. In Panels A to D, the information intensity measure II is lagged by one to four quarters respectively. We form an equal-weighted fund portfolio within each group and report its next-month after-expense four-factor alpha, in percentage points.

	II lagged by one quarter						II lagged by two quarters					
Past Alpha	1-Low	2	3	4	5-High	High-Low	1-Low	2	3	4	5-High	High-Low
1-Low	-0.151***	-0.157***	-0.145**	-0.259***	-0.244***	-0.093	-0.186***	-0.161***	-0.211***	-0.183***	-0.271***	-0.084
	(-2.65)	(-3.43)	(-2.51)	(-4.14)	(-3.46)	(-1.09)	(-3.41)	(-3.09)	(-3.65)	(-3.11)	(-3.83)	(-1.02)
2	-0.122***	-0.122***	-0.078*	-0.109**	-0.086	0.037	-0.108***	-0.091***	-0.128***	-0.076	-0.078	0.031
	(-3.48)	(-3.78)	(-1.83)	(-2.18)	(-1.42)	(0.54)	(-3.19)	(-2.78)	(-2.93)	(-1.55)	(-1.30)	(0.47)
3	-0.115***	-0.125***	-0.099***	-0.086*	0.020	0.134**	-0.119***	-0.106***	-0.133***	-0.073	0.048	0.167***
	(-3.59)	(-4.05)	(-2.80)	(-1.82)	(0.35)	(2.13)	(-3.60)	(-3.46)	(-3.63)	(-1.55)	(0.84)	(2.61)
4	-0.117***	-0.135***	-0.075*	-0.056	0.023	0.141**	-0.118***	-0.118***	-0.090**	-0.040	0.027	0.145**
	(-3.35)	(-4.12)	(-1.83)	(-1.24)	(0.46)	(2.32)	(-3.28)	(-3.45)	(-2.33)	(-0.92)	(0.53)	(2.40)
5-High	-0.116*	-0.087*	-0.045	0.091	0.201***	0.317***	-0.088	-0.117**	-0.007	0.074	0.163***	0.250***
	(-1.65)	(-1.65)	(-0.91)	(1.62)	(3.34)	(3.81)	(-1.32)	(-2.15)	(-0.15)	(1.35)	(2.71)	(3.12)
High-Low	0.035	0.070	0.100	0.350***	0.445***	0.410***	0.099	0.045	0.203***	0.256***	0.433***	0.335***
	(0.45)	(1.00)	(1.36)	(4.37)	(6.02)	(4.40)	(1.32)	(0.61)	(2.80)	(3.48)	(5.68)	(3.60)
	II lagged by three quarters						II lagged by four quarters					
Past Alpha	1-Low	2	3	4	5-High	High-Low	1-Low	2	3	4	5-High	High-Low
1-Low	-0.145**	-0.196***	-0.181***	-0.224***	-0.250***	-0.105	-0.137**	-0.166***	-0.194***	-0.203***	-0.244***	-0.107
	(-2.41)	(-4.11)	(-3.08)	(-3.85)	(-3.54)	(-1.27)	(-2.39)	(-3.33)	(-3.43)	(-3.52)	(-3.52)	(-1.37)
2	-0.103***	-0.112***	-0.063	-0.082*	-0.104*	-0.001	-0.109***	-0.106***	-0.069*	-0.073	-0.080	0.029
	(-3.21)	(-3.32)	(-1.47)	(-1.71)	(-1.76)	(-0.02)	(-3.24)	(-2.96)	(-1.66)	(-1.53)	(-1.28)	(0.43)
3	-0.113***	-0.106***	-0.122***	-0.035	-0.011	0.102*	-0.139***	-0.074**	-0.077**	-0.082*	0.008	0.147**
	(-3.48)	(-3.64)	(-3.18)	(-0.77)	(-0.20)	(1.66)	(-4.45)	(-2.35)	(-2.14)	(-1.80)	(0.16)	(2.43)
4	-0.118***	-0.108***	-0.083**	-0.051	0.006	0.124**	-0.127***	-0.097***	-0.070*	-0.047	0.004	0.131**
	(-3.55)	(-3.28)	(-2.19)	(-1.17)	(0.12)	(2.13)	(-3.71)	(-3.28)	(-1.72)	(-1.07)	(0.08)	(2.21)
5-High	-0.130*	-0.040	0.011	0.058	0.164***	0.294***	-0.113*	-0.095*	-0.002	0.072	0.138**	0.251***
	(-1.90)	(-0.78)	(0.22)	(1.04)	(2.78)	(3.65)	(-1.70)	(-1.91)	(-0.03)	(1.31)	(2.31)	(3.21)
High-Low	0.015	0.156**	0.192**	0.281***	0.414***	0.399***	0.024	0.071	0.192**	0.275***	0.382***	0.358***
	(0.18)	(2.46)	(2.49)	(3.83)	(5.38)	(3.97)	(0.29)	(1.08)	(2.53)	(3.85)	(5.06)	(3.71)

Table 1.8: Subperiod Performance of Fund Portfolios Double-Sorted by Past Alpha and Information Intensity

This table reports the after-expense four-factor alpha (in percentage points) for each of the 5 by 5 portfolios formed in independent double-sorts by past alpha and information intensity II. Past alpha is estimated from the four-factor model using past 12 months of after-expense fund returns. Panel A is for the subperiod of 1980-1996 and Panel B is for the subperiod of 1997-2014.

Panel A: 1980-1996

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.097	-0.083	-0.062	-0.165**	-0.221***	-0.124
	(-1.19)	(-1.15)	(-0.71)	(-2.04)	(-2.76)	(-1.18)
2	-0.079	-0.087*	-0.075	-0.019	-0.164**	-0.085
	(-1.50)	(-1.87)	(-1.48)	(-0.31)	(-2.21)	(-0.93)
3	-0.055	-0.100**	-0.081	0.011	0.106	0.161**
	(-1.24)	(-2.26)	(-1.62)	(0.18)	(1.47)	(2.10)
4	-0.081	-0.116**	-0.070	0.013	0.153**	0.233***
	(-1.48)	(-2.19)	(-1.21)	(0.19)	(2.50)	(2.87)
5-High	-0.155*	-0.028	-0.056	0.199**	0.311***	0.466***
	(-1.70)	(-0.35)	(-0.77)	(2.53)	(3.71)	(4.12)
High-Low	-0.058	0.056	0.006	0.363***	0.532***	0.591***
	(-0.50)	(0.54)	(0.05)	(3.32)	(4.52)	(3.89)

Panel B: 1997-2014

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.226***	-0.202***	-0.202***	-0.224***	-0.163	0.062
	(-2.93)	(-3.75)	(-3.01)	(-2.63)	(-1.56)	(0.50)
2	-0.134***	-0.154***	-0.101*	-0.096	-0.050	0.083
	(-2.95)	(-4.11)	(-1.78)	(-1.38)	(-0.55)	(0.80)
3	-0.161***	-0.108***	-0.050	-0.044	-0.033	0.129
	(-4.00)	(-3.09)	(-1.00)	(-0.67)	(-0.40)	(1.38)
4	-0.111**	-0.084**	-0.058	-0.039	-0.010	0.101
	(-2.29)	(-2.29)	(-1.23)	(-0.65)	(-0.12)	(1.10)
5-High	-0.117	-0.072	0.036	0.104	0.189**	0.306**
	(-1.12)	(-0.92)	(0.55)	(1.20)	(2.28)	(2.56)
High-Low	0.108	0.130	0.239***	0.328***	0.352***	0.244*
	(1.02)	(1.43)	(2.60)	(2.71)	(3.77)	(1.96)

Table 1.9: Performance of Fund Portfolios Under Alternative Double-Sorts

This table reports the performance of fund portfolios under alternative independent double sorts. The performance measure is the after-expense four factor alpha, in percentage points. In Panel A, funds are double-sorted by past alpha and STDEV. In Panel B, funds are double-sorted by past alpha and R2. In Panel C, funds are also double-sorted by past alpha and R2, where R2 are censored at the top and bottom 1% and the sample period is from 1990 to 2010. Past alpha is estimated using past 12 month's data under the Carhart four-factor model. STDEV is the weighted average return volatility of stocks held by a fund. R2 is the regression R-square of the Carhart four-factor model using past 24 months of returns.

Panel A: Funds double-sorted by past alpha and STDEV

	STDEV					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.072	-0.090**	-0.167***	-0.236***	-0.390***	-0.315***
	(-1.21)	(-2.05)	(-3.80)	(-4.72)	(-5.52)	(-3.38)
2	-0.065*	-0.073**	-0.096**	-0.188***	-0.231***	-0.166**
	(-1.68)	(-2.30)	(-2.54)	(-4.19)	(-3.47)	(-2.10)
3	-0.029	-0.111***	-0.082**	-0.096**	-0.130*	-0.101
	(-0.79)	(-3.73)	(-2.33)	(-2.11)	(-1.83)	(-1.21)
4	-0.012	-0.047	-0.053	-0.055	-0.121*	-0.109
	(-0.28)	(-1.36)	(-1.41)	(-1.21)	(-1.76)	(-1.32)
5-High	0.016	0.041	0.051	0.114**	0.062	0.044
	(0.29)	(0.81)	(1.00)	(2.06)	(0.79)	(0.45)
High-Low	0.085	0.131**	0.218***	0.349***	0.452***	0.365***
	(1.21)	(2.35)	(3.91)	(5.80)	(6.07)	(3.93)

Panel B: Funds double-sorted by past alpha and R2

	R2					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.261***	-0.204***	-0.225***	-0.192***	-0.185***	0.077
	(-3.56)	(-3.17)	(-3.97)	(-3.82)	(-4.31)	(1.08)
2	-0.066	-0.114**	-0.090**	-0.136***	-0.137***	-0.071
	(-1.18)	(-2.34)	(-2.28)	(-3.81)	(-4.69)	(-1.26)
3	-0.061	-0.029	-0.077**	-0.085***	-0.119***	-0.058
	(-1.11)	(-0.61)	(-2.07)	(-2.76)	(-4.29)	(-1.08)
4	0.009	-0.033	-0.044	-0.094***	-0.095***	-0.104*
	(0.16)	(-0.73)	(-1.17)	(-2.61)	(-3.01)	(-1.82)
5-High	0.125	0.096	0.012	-0.049	-0.047	-0.172**
	(1.60)	(1.50)	(0.24)	(-1.04)	(-1.03)	(-2.03)
High-Low	0.386***	0.300***	0.237***	0.142**	0.138***	-0.249***
	(3.82)	(3.41)	(3.37)	(2.28)	(2.68)	(-2.59)

Panel C: Funds double-sorted by past alpha and censored R2 (1990-2010)

	R2					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.252**	-0.228**	-0.249***	-0.234***	-0.243***	0.009
	(-2.56)	(-2.56)	(-3.35)	(-3.39)	(-4.57)	(0.09)
2	0.029	-0.101	-0.072	-0.162***	-0.151***	-0.180**
	(0.39)	(-1.52)	(-1.31)	(-3.26)	(-4.17)	(-2.43)
3	0.041	-0.054	-0.077	-0.082**	-0.141***	-0.182***
	(0.61)	(-0.88)	(-1.61)	(-2.05)	(-4.18)	(-2.66)
4	0.077	0.001	-0.013	-0.100**	-0.110***	-0.187**
	(1.08)	(0.02)	(-0.25)	(-2.13)	(-2.87)	(-2.47)
5-High	0.275**	0.157*	0.008	-0.046	-0.074	-0.349***
	(2.57)	(1.69)	(0.11)	(-0.68)	(-1.16)	(-2.91)
High-Low	0.527***	0.385***	0.257***	0.188**	0.170***	-0.357***
	(4.00)	(3.08)	(2.59)	(2.20)	(2.62)	(-2.84)

Panel D: Funds double-sorted by past alpha and Skewness

	Skewness					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.160**	-0.218***	-0.197***	-0.161***	-0.345***	-0.185**
	(-2.46)	(-4.08)	(-3.69)	(-2.94)	(-5.12)	(-2.44)
2	-0.061	-0.066*	-0.130***	-0.154***	-0.126**	-0.065
	(-1.42)	(-1.89)	(-3.25)	(-3.59)	(-2.17)	(-1.05)
3	-0.005	-0.090***	-0.107***	-0.064	-0.100*	-0.096
	(-0.11)	(-2.90)	(-3.22)	(-1.54)	(-1.78)	(-1.41)
4	-0.015	-0.020	-0.103***	-0.072*	-0.074	-0.058
	(-0.34)	(-0.56)	(-2.99)	(-1.91)	(-1.41)	(-0.85)
5-High	0.161**	0.114*	0.050	0.005	0.073	-0.088
	(2.16)	(1.93)	(0.83)	(0.10)	(1.35)	(-1.10)
High-Low	0.321***	0.332***	0.248***	0.166**	0.419***	0.097
	(3.55)	(4.24)	(3.20)	(2.26)	(5.99)	(1.12)

Table 1.10: Controlling for Competing Effects with Triple-Sorted Fund Portfolios

This table reports the performance of fund portfolios resulting from a triple-sorting procedure that examines the effect of II on performance persistence while controlling for competing effects. Fund performance is measured by after-expense four-factor alpha, in percentage points. Each month, we first sort funds into quintiles first based on a fund characteristic representing a competing effect. Then, within each quintile we further independently sort funds into 25 (5 by 5) groups based on past alpha and II. Finally, we combine funds in the same quintiles of past-alpha and II but from different quintile ranks of the first sorting variable into one single equal-weighted portfolio. This procedure resulting in 25 fund portfolios with different past alpha and II but with relatively even distribution of the controlled fund characteristic (i.e., the first sorting variable). The controlled effects include SIZESCORE, ILLIQSCORE, R2, ActiveShare, and STDEV.

Panel A: Controlling for SIZESCORE

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.213***	-0.230***	-0.161***	-0.134***	-0.215***	-0.002
	(-3.47)	(-4.80)	(-3.15)	(-2.62)	(-3.78)	(-0.03)
2	-0.201***	-0.134***	-0.093**	-0.101**	-0.091*	0.110*
	(-4.17)	(-3.30)	(-2.34)	(-2.31)	(-1.89)	(1.81)
3	-0.169***	-0.115***	-0.059	-0.069*	0.007	0.176***
	(-3.81)	(-2.84)	(-1.55)	(-1.72)	(0.16)	(3.05)
4	-0.088*	-0.134***	-0.058	-0.063*	0.043	0.132**
	(-1.90)	(-3.46)	(-1.58)	(-1.69)	(1.02)	(2.10)
5-High	-0.084	0.006	0.042	0.086*	0.158***	0.242***
	(-1.28)	(0.13)	(0.91)	(1.74)	(3.13)	(3.24)
High-Low	0.129*	0.236***	0.203***	0.220***	0.373***	0.244***
	(1.67)	(3.74)	(3.23)	(3.56)	(5.72)	(3.16)

Panel B: Controlling for ILLIQSCORE

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.197***	-0.230***	-0.195***	-0.161***	-0.180***	0.017
	(-3.55)	(-4.51)	(-3.79)	(-2.83)	(-2.61)	(0.21)
2	-0.147***	-0.100***	-0.132***	-0.092**	-0.082	0.064
	(-3.59)	(-2.75)	(-3.22)	(-2.04)	(-1.43)	(0.93)
3	-0.120***	-0.101***	-0.118***	-0.042	-0.031	0.089
	(-3.33)	(-3.05)	(-3.28)	(-1.01)	(-0.59)	(1.44)
4	-0.110**	-0.076**	-0.057*	-0.062	-0.006	0.104
	(-2.54)	(-2.05)	(-1.70)	(-1.43)	(-0.11)	(1.49)
5-High	-0.079	-0.033	0.057	0.095*	0.163***	0.242***
	(-1.14)	(-0.64)	(1.22)	(1.93)	(2.71)	(2.80)
High-Low	0.118	0.198***	0.252***	0.256***	0.342***	0.225**
	(1.58)	(2.90)	(3.70)	(3.98)	(4.82)	(2.55)

Panel C: Controlling for ActiveShare

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.231***	-0.187***	-0.165***	-0.219***	-0.196***	0.035
	(-3.78)	(-3.67)	(-3.32)	(-4.14)	(-3.17)	(0.45)
2	-0.161***	-0.111**	-0.064	-0.099**	-0.125**	0.036
	(-3.22)	(-2.46)	(-1.44)	(-2.04)	(-2.41)	(0.55)
3	-0.122***	-0.095**	-0.128***	-0.056	-0.009	0.113*
	(-2.76)	(-2.22)	(-3.18)	(-1.31)	(-0.18)	(1.80)
4	-0.103**	-0.094**	-0.051	-0.028	-0.005	0.098
	(-2.28)	(-2.19)	(-1.19)	(-0.70)	(-0.11)	(1.64)
5-High	-0.101	0.015	0.046	0.040	0.135**	0.235***
	(-1.46)	(0.28)	(1.00)	(0.83)	(2.53)	(2.99)
High-Low	0.130	0.201***	0.211***	0.259***	0.331***	0.200**
	(1.61)	(2.93)	(3.20)	(3.82)	(4.86)	(2.32)

Panel D: Controlling for R2

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.188***	-0.117**	-0.167***	-0.259***	-0.277***	-0.089
	(-3.54)	(-2.43)	(-3.11)	(-4.12)	(-4.09)	(-1.12)
2	-0.109***	-0.115***	-0.101**	-0.056	-0.159***	-0.050
	(-2.91)	(-3.34)	(-2.51)	(-1.17)	(-2.60)	(-0.74)
3	-0.123***	-0.109***	-0.109***	-0.025	-0.010	0.113**
	(-3.84)	(-3.31)	(-2.74)	(-0.54)	(-0.20)	(2.05)
4	-0.094**	-0.106***	-0.044	-0.025	0.022	0.116**
	(-2.39)	(-3.29)	(-1.08)	(-0.52)	(0.44)	(1.97)
5-High	-0.091	-0.098*	-0.003	0.129**	0.120**	0.211***
	(-1.38)	(-1.83)	(-0.06)	(2.50)	(2.24)	(2.92)
High-Low	0.097	0.019	0.165**	0.388***	0.397***	0.299***
	(1.32)	(0.27)	(2.34)	(5.49)	(5.42)	(3.34)

Panel E: Controlling for STDEV

	II					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.226***	-0.220***	-0.188***	-0.187***	-0.222***	0.004
	(-4.51)	(-5.22)	(-4.45)	(-3.84)	(-3.93)	(0.06)
2	-0.191***	-0.131***	-0.112***	-0.091**	-0.101*	0.090
	(-4.53)	(-3.94)	(-3.29)	(-2.31)	(-1.85)	(1.46)
3	-0.107***	-0.107***	-0.079**	-0.095**	-0.014	0.093
	(-2.62)	(-3.05)	(-2.33)	(-2.36)	(-0.27)	(1.45)
4	-0.082*	-0.086**	-0.080**	-0.040	-0.005	0.077
	(-1.78)	(-2.35)	(-2.10)	(-0.95)	(-0.10)	(1.09)
5-High	-0.037	-0.040	0.060	0.062	0.124**	0.161**
	(-0.59)	(-0.76)	(1.26)	(1.22)	(2.40)	(2.17)
High-Low	0.189***	0.180***	0.248***	0.248***	0.346***	0.157**
	(2.65)	(3.01)	(4.60)	(4.59)	(7.44)	(2.03)

Table 1.11: Fama-MacBeth Multivariate Regressions

This table reports results of Fama-MacBeth regressions that analyze the impact of information intensity on performance persistence. The dependent variable is the fund four-factor abnormal return. In Panel A, the main explanatory variables include past alpha, II, and their interactions. The control variables include Log(TNA), expense ratio, Log(Age), fund turnover, lagged flow, two proxies for the effects of market frictions –SIZESCORE and ILLIQSCORE, the fund activeness measure ActiveShare, as well as the interaction terms of past alpha with SIZESCORE, ILLIQSCORE, and ActiveShare. In Panel B, the main explanatory variables include the five past-alpha dummies (past $\alpha 1$ to past $\alpha 5$) for funds in the five past-alpha quintiles, II, and the interactions of II with the five past-alpha dummies. The control variables include STDEV, TR, and their interactions with past alpha dummies, as well as Log(TNA), expense ratio, Log(Age), fund turnover, and lagged fund flow. Variables involved in the interaction terms, including past alpha, II, SIZESCORE, ILLIQSCORE, ActiveShare, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

Panel A: Controlling for SIZESCORE, ILLIQSCORE, and ActiveShare

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1981-2012)	[5] (1980-2014)	[6] (1981-2012)
Log(TNA)	-0.0184***	-0.0176***	-0.0182***	-0.0169**	-0.0175***	-0.0173***
	(-3.02)	(-2.93)	(-2.98)	(-2.54)	(-2.89)	(-2.66)
Fee	-0.1182***	-0.1194***	-0.1145***	-0.1123***	-0.1165***	-0.1085***
	(-5.40)	(-5.67)	(-5.36)	(-5.22)	(-5.60)	(-5.16)
Log(Age)	-0.0072	-0.0081	-0.0064	-0.0091	-0.0072	-0.0073
	(-0.99)	(-1.16)	(-0.89)	(-1.24)	(-1.04)	(-1.02)
Turnover	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.62)	(-0.60)	(-0.63)	(-0.58)	(-0.56)	(-0.52)
Lagged Flow	-0.0017	-0.0021	-0.0017	-0.0027	-0.0019	-0.0028
	(-0.44)	(-0.55)	(-0.46)	(-0.69)	(-0.52)	(-0.72)
Past α	0.0990***	0.0922***	0.0981***	0.0928***	0.0916***	0.0930***
	(5.48)	(5.34)	(5.42)	(5.15)	(5.32)	(5.25)
II	0.0260**	0.0203	0.0244*	0.0245*	0.0202	0.0224
	(1.96)	(1.33)	(1.68)	(1.70)	(1.27)	(1.36)
II * Past α	0.0279***	0.0249***	0.0271***	0.0283***	0.0244**	0.0272***
	(3.18)	(2.65)	(2.90)	(2.87)	(2.49)	(2.64)
SIZESCORE		-0.0096			-0.0108	-0.0119
		(-0.51)			(-0.56)	(-0.60)
SIZESCORE * Past α		-0.0114			-0.0113	-0.0161
		(-1.15)			(-1.14)	(-1.18)
ILLIQSCORE			0.0024		-0.0018	-0.0076
			(0.24)		(-0.18)	(-0.73)
ILLIQSCORE * Past α			0.0036		0.0032	0.0038
			(0.43)		(0.38)	(0.43)
ActiveShare				0.0061		-0.0026
				(0.38)		(-0.23)
ActiveShare * Past α				0.0109		-0.0046
				(1.01)		(-0.34)
R-square	0.09	0.11	0.10	0.11	0.12	0.13

Panel B: Controlling for STDEV and TR

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1980-2014)
log(TNA)	-0.0171***	-0.0149***	-0.0153***	-0.0142***
	(-2.80)	(-2.66)	(-2.62)	(-2.58)
Fee	-0.1194***	-0.1027***	-0.1296***	-0.1115***
	(-5.53)	(-5.27)	(-5.93)	(-5.75)
Age	-0.0080	-0.0129*	-0.0139**	-0.0170***
	(-1.11)	(-1.89)	(-2.11)	(-2.68)
Turnover	-0.0001	0.0000	-0.0001	0.0000
	(-0.95)	(-0.03)	(-0.88)	(0.02)
Flow	-0.0015	-0.0023	-0.0016	-0.0022
	(-0.39)	(-0.64)	(-0.41)	(-0.63)
Past $\alpha 1$	0.0634	0.0703	0.2051	0.4321**
	(1.00)	(1.12)	(1.17)	(2.21)
Past $\alpha 2$	0.1625***	0.1376**	0.4508***	0.5017***
	(2.62)	(2.26)	(3.10)	(2.96)
Past $\alpha 3$	0.1926***	0.1673***	0.1935	0.2673*
	(3.08)	(2.72)	(1.36)	(1.73)
Past $\alpha 4$	0.2232***	0.2000***	0.0875	0.1337
	(3.61)	(3.28)	(0.59)	(0.77)
Past $\alpha 5$	0.3185***	0.3012***	0.0988	0.0593
	(4.85)	(4.65)	(0.55)	(0.30)
II * Past $\alpha 1$	-0.0269	0.0255	-0.0089	0.0198
	(-1.34)	(1.11)	(-0.80)	(1.59)
II * Past $\alpha 2$	0.0027	0.0177	0.0010	0.0098
	(0.17)	(0.92)	(0.10)	(0.91)
II * Past $\alpha 3$	0.0264*	0.0436**	0.0120	0.0203**
	(1.71)	(2.49)	(1.38)	(2.07)
II * Past $\alpha 4$	0.0285*	0.0485***	0.0179**	0.0296***
	(1.92)	(2.69)	(2.00)	(2.83)
II * Past $\alpha 5$	0.0724***	0.0607***	0.0410***	0.0357***
	(3.66)	(2.63)	(3.69)	(2.78)
STDEV * Past $\alpha 1$		-0.0971***		-0.0025***
		(-3.12)		(-3.86)
STDEV * Past $\alpha 2$		-0.0411		-0.0010*
		(-1.34)		(-1.65)
STDEV * Past $\alpha 3$		-0.0482		-0.0009
		(-1.60)		(-1.43)
STDEV * Past $\alpha 4$		-0.0502		-0.0012*
		(-1.61)		(-1.83)
STDEV * Past $\alpha 5$		-0.0103		0.0000
		(-0.31)		(-0.06)
TR * Past $\alpha 1$			-0.0055	0.0038
			(-0.14)	(0.10)
TR * Past $\alpha 2$			-0.0901***	-0.0759**
			(-2.60)	(-2.22)
TR * Past $\alpha 3$			-0.0233	-0.0201
			(-0.71)	(-0.63)
TR * Past $\alpha 4$			0.0056	0.0235
			(0.17)	(0.74)
TR * Past $\alpha 5$			-0.0435	-0.0293
			(-1.00)	(-0.71)
R-squared	0.15	0.19	0.18	0.22

Table 1.12: Event Window Performance of Funds Double-Sorted by Past Alpha and Information Intensity

This table reports the event-window performance of fund portfolios double-sorted by past alpha and II. In each quarter, funds are sorted into 25 (5 by 5) equal-weighted portfolios independently by past alpha and II. Fund event-window performance is the weighted average event-window returns during a given quarter over stocks held by a fund. The event-window return of a stock is the stock return during a 5-day window (two days before to two days after) around two types of corporate events: earnings announcements and M&A announcements. Panel A reports the event-window performance during the four quarters prior to fund ranking. Panel B reports the event-window performance during the quarter after fund ranking.

Panel A: Event-window performance during prior four quarters

	Information Intensity					
Past *Alpha*	1-Low	2	3	4	5-High	High-Low
1-Low	-0.074***	-0.067***	-0.035	-0.033	-0.100***	-0.026
	(-2.62)	(-2.71)	(-1.38)	(-1.21)	(-3.44)	(-0.72)
2	-0.031	-0.018	-0.008	0.055**	0.016	0.046
	(-1.41)	(-0.93)	(-0.38)	(2.24)	(0.58)	(1.45)
3	0.004	0.005	0.062***	0.088***	0.106***	0.102***
	(0.19)	(0.33)	(3.09)	(4.51)	(3.71)	(3.11)
4	0.038**	0.061***	0.085***	0.111***	0.182***	0.144***
	(2.00)	(3.27)	(4.33)	(4.59)	(6.53)	(4.44)
5-High	0.077**	0.146***	0.200***	0.233***	0.251***	0.174***
	(2.48)	(5.39)	(6.78)	(7.47)	(7.53)	(4.29)
High-Low	0.151***	0.213***	0.234***	0.266***	0.351***	0.200***
	(4.06)	(6.18)	(6.56)	(6.86)	(10.35)	(4.33)

Panel B: Event-window performance during subsequent quarter

	Information Intensity					
Past *Alpha*	1-Low	2	3	4	5-High	High-Low
1-Low	0.005	0.052**	0.052**	0.074***	0.044	0.040
	(0.17)	(2.35)	(2.19)	(2.97)	(1.49)	(0.97)
2	-0.021	0.003	0.053***	0.069**	0.069**	0.090**
	(-1.03)	(0.13)	(2.61)	(2.56)	(2.18)	(2.47)
3	0.021	0.010	0.040**	0.098***	0.128***	0.107***
	(0.91)	(0.51)	(2.16)	(4.06)	(4.90)	(3.08)
4	0.006	0.001	0.034	0.098***	0.109***	0.103***
	(0.28)	(0.06)	(1.50)	(4.15)	(3.65)	(3.02)
5-High	0.002	0.030	0.083***	0.140***	0.133***	0.131***
	(0.08)	(1.01)	(3.02)	(4.65)	(4.50)	(3.44)
High-Low	-0.002	-0.022	0.031	0.067**	0.089***	0.091*
	(-0.05)	(-0.66)	(0.98)	(1.99)	(3.07)	(1.76)

Table 1.13: Fund Flow Response

This table reports the results of Fama-MacBeth regressions that analyze the effect of information intensity on flow-performance sensitivity. The dependent variable is the quarterly fund flow expressed in percentage points. In Panel A, the main explanatory variables include past fund alpha and II, and their interaction term. The control variables include Log(TNA), expense ratio, Log(Age), fund turnover, lagged flow, two proxies for the effects of market frictions –SIZESCORE and ILLIQSCORE, the fund activeness measure ActiveShare, as well as the interaction terms of past alpha with SIZESCORE, ILLIQSCORE, and ActiveShare. In Panel B, the main explanatory variables include the five past-alpha dummies (past $\alpha 1$ to past $\alpha 5$) for funds in the five past-alpha quintiles, II, and the interactions of II with the five past-alpha dummies. The control variables include STDEV, TR, and their interactions with past alpha dummies, as well as Log(TNA), expense ratio, Log(Age), fund turnover, and lagged fund flow. Variables involved in the interaction terms, including past alpha, II, SIZESCORE, ILLIQSCORE, ActiveShare, STDEV, and TR, are cross-sectionally standardized before used in the regressions.

Panel A: Controlling for SIZESCORE, ILLIQSCORE, and ActiveShare

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1981-2012)	[5] (1980-2014)	[6] (1981-2012)
Log(TNA)	-0.1734***	-0.1819***	-0.1733***	-0.1689***	-0.1800***	-0.2039***
	(-3.35)	(-3.54)	(-3.39)	(-3.01)	(-3.54)	(-3.53)
Fee	-0.0028	-0.0384	-0.0095	0.0249	-0.0369	0.0053
	(-0.02)	(-0.21)	(-0.05)	(0.13)	(-0.20)	(0.03)
Log(Age)	-1.2253***	-1.1837***	-1.2164***	-1.2406***	-1.1841***	-1.2156***
	(-14.13)	(-13.69)	(-14.46)	(-13.59)	(-14.02)	(-13.69)
Turnover	0.0036**	0.0030**	0.0033**	0.0038**	0.0030**	0.0034**
	(2.39)	(2.10)	(2.27)	(2.45)	(2.07)	(2.19)
Lagged Flow	0.2109***	0.2087***	0.2096***	0.2163***	0.2078***	0.2139***
	(11.92)	(11.79)	(11.80)	(11.61)	(11.72)	(11.44)
Past α	1.6943***	1.7364***	1.7062***	1.7958***	1.7467***	1.8329***
	(14.26)	(15.04)	(14.68)	(14.01)	(15.08)	(13.93)
II	0.1878*	0.0449	0.0141	0.1838*	-0.0716	-0.0170
	(1.77)	(0.46)	(0.14)	(1.73)	(-0.74)	(-0.17)
II * Past α	0.1624**	0.1493*	0.1580*	0.1884**	0.1508	0.1773
	(2.29)	(1.69)	(1.84)	(2.19)	(1.52)	(1.61)
SIZESCORE		-0.2528***			-0.2113**	-0.3251***
		(-2.59)			(-2.18)	(-2.78)
SIZESCORE * Past α		0.0247			0.0429	-0.0680
		(0.26)			(0.44)	(-0.48)
ILLIQSCORE			0.3417***		0.2929***	0.3108***
			(3.96)		(3.36)	(3.42)
ILLIQSCORE * Past α			0.0464		0.0538	0.0507
			(0.61)		(0.68)	(0.59)
ActiveShare				0.0683		-0.1917*
				(0.72)		(-1.78)
ActiveShare * Past α				-0.1029		-0.1809
				(-1.08)		(-1.33)
R-square	0.14	0.15	0.15	0.15	0.15	0.16

Panel B: Controlling for STDEV and TR

	[1] (1980-2014)	[2] (1980-2014)	[3] (1980-2014)	[4] (1980-2014)
log(TNA)	-0.1646***	-0.1877***	-0.1043**	-0.1214**
	(-3.27)	(-3.86)	(-2.16)	(-2.55)
Fee	-0.0904	-0.1368	-0.0938	-0.1092
	(-0.51)	(-0.81)	(-0.52)	(-0.62)
Age	-1.2271***	-1.2634***	-1.0408***	-1.0638***
	(-13.69)	(-14.22)	(-12.30)	(-12.64)
Turnover	0.0033**	0.0036**	0.0036**	0.0038**
	(2.18)	(2.45)	(2.34)	(2.56)
Flow	0.2140***	0.2108***	0.2222***	0.2179***
	(11.93)	(11.70)	(11.55)	(11.27)
Past $\alpha 1$	5.5607***	5.9021***	4.2903***	4.5126***
	(8.41)	(8.84)	(6.92)	(7.20)
Past $\alpha 2$	6.7840***	7.0644***	5.4405***	5.6198***
	(10.53)	(10.92)	(9.13)	(9.36)
Past $\alpha 3$	7.3436***	7.6675***	6.1004***	6.3154***
	(11.47)	(11.76)	(10.02)	(10.25)
Past $\alpha 4$	8.1739***	8.4804***	6.7172***	6.9001***
	(12.30)	(12.66)	(10.75)	(10.90)
Past $\alpha 5$	10.3046***	10.4799***	8.7623***	8.8017***
	(15.22)	(15.28)	(13.95)	(13.94)
II * Past $\alpha 1$	-0.0095	0.0506	-0.0105	0.0629
	(-0.07)	(0.32)	(-0.09)	(0.44)
II * Past $\alpha 2$	-0.1396	-0.0855	-0.0323	0.0722
	(-0.98)	(-0.57)	(-0.27)	(0.54)
II * Past $\alpha 3$	0.0081	-0.0894	0.0244	-0.0392
	(0.06)	(-0.55)	(0.19)	(-0.24)
II * Past $\alpha 4$	0.0850	0.1796	0.1190	0.2421
	(0.63)	(1.13)	(0.93)	(1.60)
II * Past $\alpha 5$	0.6694***	0.6929**	0.7904***	0.7290***
	(2.88)	(2.43)	(3.29)	(2.59)
STDEV * Past $\alpha 1$		0.0029		-0.0125
		(0.02)		(-0.07)
STDEV * Past $\alpha 2$		-0.1704		-0.2337
		(-1.04)		(-1.54)
STDEV * Past $\alpha 3$		0.1126		0.0983
		(0.58)		(0.53)
STDEV * Past $\alpha 4$		-0.2616		-0.2985
		(-1.34)		(-1.56)
STDEV * Past $\alpha 5$		-0.4870		-0.3067
		(-1.58)		(-0.98)
TR * Past $\alpha 1$			-0.1593	-0.1737
			(-1.15)	(-1.27)
TR * Past $\alpha 2$			-0.0819	-0.0743
			(-0.58)	(-0.53)
TR * Past $\alpha 3$			-0.1497	-0.1248
			(-0.83)	(-0.69)
TR * Past $\alpha 4$			-0.0043	0.0575
			(-0.04)	(0.47)
TR * Past $\alpha 5$			-0.6054***	-0.5168***
			(-3.37)	(-3.05)
R-squared	0.17	0.18	0.18	0.20

Chapter 2
Playing Favorites? A Closer Look at IPO Allocations to Investment Bank-Affiliated Mutual Funds

2.1 Introduction

Two facts explain the great attention paid to IPO allocations by both the financial media and the academic world. One is persistently large underpricing of IPOs. The other is investment banks' full discretion over IPO allocations. Adding that some IPO investors are affiliated with investment banks does not help dampen the popular interest. Anecdotal stories depict an often complicated relationship between the underwriting arm and the fund management arm of an investment bank. On the one hand, an investment bank would like to see its fund management business thrive by giving it a little performance boost through allocations of underpriced IPOs because investor money chases performance (Sirri and Tufano (1998)). On the other hand, an investment bank has all the incentives to complete an IPO underwriting even in a situation where investor demand is low. Affiliated mutual funds could serve as the last resort to absorb any unmarketable IPO shares. This creates a conflict of interest as mutual fund serves the best interest of its shareholders not of its parent company.[1] Wall Street Journal reported a contentious argument between an investment banker and a fund manager during which the investment banker asked the fund manager to be a "team player" in helping buying a client's IPO offerings.[2] Bloomberg reported that mutual funds affiliated with major Wall Street investment banks invested disproportionately large amount of assets

[1] Indeed, Section 10(f) of the Investment Company Act initially "...prohibits a registered fund from knowingly purchasing any security for which an underwriter having certain relationships with its investment adviser is acting as a principal underwriter...". On the grounds of equal access to investment opportunities, the banks lobbied the SEC to adopt Rule 10(f)-3 that permits an affiliated fund to purchase securities from the underwriting syndicate if certain conditions are met. These conditions are discussed in Section 2 of this paper.

[2] *Mutual funds and IPO bankers danced close*, by Aaron Lucchetti, The Wall Street Journal, March 12, 2003.

in their clients' IPO offerings compared to non-affiliated institutional investors.[3] When it comes to the allocation of IPO shares within the fund families, it is not without controversies either. A Wall Street Journal article reported that some fund families diverted IPO share allocations to smaller funds in order to lift their performance.[4]

Researchers have paid attention to these types of conflict of interest in IPO share allocations. In a seminal study, Ritter and Zhang (2007) find no substantive evidence that investment banks use affiliated mutual funds as dumping ground for unmarketable or cold IPOs. Instead, they find some evidence supporting the nepotism hypothesis that IPOs allocated to affiliated mutual funds are often over-subscribed and have higher first-day returns. Gaspar, Massa, and Matos (2006) study IPO share allocations within fund families and find that fund families often allocate hot IPOs to high-fee and better-performing funds, consistent with a family-level strategy of cultivating "star funds".

One limitation to these prior studies, however, is that they use the periodically-reported fund holdings to approximate the actual IPO shares allocated to funds. Mutual funds are mandated to report holdings on a quarterly or semi-annual frequency.[5] Thus, there could be a time gap of up to six months between an IPO date and the date of reported fund holdings.[6] Indeed, Ritter and Zhang (2007) acknowledge that "[t]he aftermarket selling and the resulting discrepancy between the reported holding and the actual allocation, however, could be

[3] *Citigroup uses mutual funds as 'dumping grounds' for clients*, by David Dietz and Adam Levy, Bloomberg, April 29, 2004.

[4] *Mutual funds can slice up IPO pies as they want, often burnishing smaller funds*, by Christopher Oster, The Wall Street Journal, May 24, 2004.

[5] The mandatory reporting frequency for fund holdings is quarterly before 1984, semi-annual between 1984 and May 2005, and quarterly again afterwards.

[6] Several other studies also use reported holdings to proxy for actual IPO allocations, such as Hanley and Wilhelm (1995), Reuter (2006), Johnson and Marietta-Westberg (2009), Chemmanur, Hu, and Huang (2010), Hao and Yan (2012), Hwang, Titman, and Wang (2015).

an important concern...".

The data on IPO shares allocated to affiliated mutual funds are actually available, as these funds are required by law to disclose such allocations in their N-SAR filings to SEC. In this study, I manually collect such data from fund disclosures, and take a closer look at the potential conflict of interest in IPO share allocations by the investment banks and by the affiliated fund management companies. My sample consists of 508 IPOs during the period of 2008–2014 of which at least one investment bank with mutual fund business participates in underwriting.[7]

I find that the actual shares received by a fund at the time of IPO can be quite different from the holdings reported at the immediate period end of the fund. In the aftermarket, funds generally increase holdings of IPOs but more of cold IPOs than hot ones. On average, at the immediate period end of the fund after IPO, holdings of hot IPOs were increased by 25%, while holdings of cold IPOs were increased by 75%.[8] This discrepancy from using reported holdings as a proxy will overestimate actual allocations, particularly for cold IPOs. The correlation between actual IPO allocations and reported holdings is 0.60.[9]

Based on the actual IPO share allocations, I have the following key findings.

[7] Another data issue is the identification of affiliated mutual funds. Ritter and Zhang (2007) use the names of the fund investment companies affiliated with the investment banks to identify affiliated mutual funds. This method likely omitted mutual funds sub-advised by investment bank-affiliated advisers. Many mutual funds sponsored by major insurance companies carry their own brand names but outsource portions of their portfolio decisions to investment bank-affiliated advisers. Out of 3,302 allocations to affiliated mutual funds during 2008 and 2014, almost one third (1,236) are allocated to sub-advised funds. Omitting this group of funds will underestimate the share of IPO allocated to affiliated advisers that have large sub-advising arrangements. In N-SAR filings, the investment bank affiliation of mutual funds are self-identified by the funds. Thus my sample avoids the above identification issue and includes the affiliated sub-advised funds.

[8] Cold IPOs are defined as IPOs with premarket price adjustment less than 0, while hot IPOs are ones with premarket price adjustment greater than or equal 0.

[9] A few prior studies have compared the actual IPO allocations and reported holdings using small datasets on IPOs, for example, Hanley and Wilhelm's (38 IPOs) and Ritter and Zhang's (11 IPOs). The correlation in my sample is in line with the comparison results reported by these studies. However, my sample of 508 IPOs is more comprehensive than theirs.

First, I find that affiliated mutual funds are able to avoid cold IPOs. Between 2008 and 2014, of the 508 IPOs underwritten by investment banks with fund management business, more than half (270 IPOs) were allocated to their affiliated mutual funds. Compared to the unallocated IPOs (238 IPOs), the allocated IPOs had higher average level of premarket demand as measured by price adjustment (3.10% vs. -8.08%),[10] higher average first-day returns (21.25% vs. 10.99%), and higher amount of money left on the table ($26.1 billion vs. $2.9 billion). Both during the entire sample period and sub-periods, Probit regression confirms a strong positive relationship between the premarket demand and the probability of affiliated mutual funds purchasing an IPO controlling for other covariates that may influence their purchase decision. This is consistent with Ritter and Zhang's findings that affiliated mutual funds as a group choose to purchase IPOs that receive higher premarket demand as measured by price adjustment and subsequently earn higher first-day returns. The evidence thus supports that the regulations (Rule 10(f)-3 of the Investment Company Act of 1940) are effective in deterring investment banks from using affiliated mutual funds as "dumping ground" for unmarketable or cold IPOs. Furthermore, affiliated fund advisers appear to take advantage of the private information produced in the IPO process and successfully avoid relatively cold IPOs entirely. This is contrary to the *quid pro quo* expectation in Hanley and Wilhelm (1995) that in order to purchase underpriced offerings institutional investors need to purchase less-attractive issues as well. Affiliated mutual funds may carry a special status that other institutional investors do not.

Second, however, among the IPO affiliated mutual funds choose to purchase, there is an

[10] Hanley (1993) first documents the phenomenon of price adjustment. IPOs with final offer price set on the upper end of the initial filing range earn higher first-day returns.

inverse relation between an IPO's premarket demand and its share of allocation to affiliated mutual funds as group. This contradicts the notion that affiliated mutual funds receive favoritism from investment banks. Within allocated IPOs (the relatively hot IPOs), affiliated mutual funds as a group are allocated less share of an IPO offering when an IPO's premarket demand is higher. During the entire sample period, a 10% increase in price adjustment results in a 0.28% decrease in allocation to affiliated mutual funds as a group. This inverse relationship is exacerbated during the Great Recession (2008–2010), with a 10% increase in price adjustment corresponding to a 0.6% decrease in allocation.

Third, I find that the patterns are consistent at the level of individual investment bank. My test results show that on average an investment bank allocate less share of an over-subscribed IPO to its affiliated mutual funds, consistent with the results from aggregated allocations at the stock level. A 10% increase in price adjustment results in a 0.36% decrease in allocation to affiliated mutual funds. This inverse relationship is negative and significant for the entire sample period and all sub-periods, and is exacerbated during the Great Recession period. A follow-up question is whether the average effect is a result of a few dominant investment banks, such as J.P. Morgan and Goldman Sachs. I divide the sample by different investment banks and run separate regressions to investigate potentially large influence by a few banks. My findings show that nearly all investment banks in the sample follow the same strategy in terms of allocating IPO shares to their affiliated mutual funds, except for one bank (Wells Fargo). For example, among IPOs allocated by J.P. Morgan, a 10% increase in price adjustment results in a 0.38% decrease in allocation. While among IPOs allocated by Goldman Sachs, a 10% increase in price adjustment results in a 0.61% decrease in allocation.

Fourth, I examine potential conflict of interest in IPO allocations within the affiliated fund families. The mutual fund literature has been paying attention to how strategically fund families allocate resources among its funds to benefit the entire family. Nanda, Wang, and Zheng (2004) hypothesizes that fund families boost the performance of "star funds" to create a spillover effect that benefits the rest of funds in the family. IPO allocations provides a clean way to test the preferential treatment fund families bestow on their star funds. Gaspar, Massa and Matos (2006) find that fund family allocates more hot IPOs to funds that charge higher fees and have better past performances. Using actual allocation data, I perform a two-step analysis. The first step is to examine which funds in the fund family are more likely to receive IPO allocations, given that on average these IPOs are relatively hot compared to unallocated ones. The second step is to examine the determinants of how much share of allocation individual fund receives. The results from the first step partially confirms Massa et. al. (2006)'s finding. Funds earning higher fees are more likely to receive IPO allocations. Good past performance measured by past alpha does not necessitate IPO allocations. But there appears to be large variations among different families in terms of how they decide which fund to receive IPO allocations. Some fund advisers allocate IPOs to funds with lower expense and lower past performance, indicating performance boost for weaker funds.

Finally, although on average "star funds" are more likely to receive IPO allocations, funds with higher expense and better past performance actually receive less share of hotter IPOs. This is contrary to Massa et. al. (2006)'s findings that "star funds" receive more shares of hotter IPOs. Fund families appear to balance the allocations of hotter IPO shares among "star funds".

My study makes several contributions. This is the first study to use actual allocations to examine how investment banks allocate IPOs to their affiliated mutual funds. Using a larger IPO sample, I provide a direct comparison between actual allocations and reported holdings. Using reported holdings will likely overestimate actual allocations, particularly for cold IPOs. Second, I corroborate Ritter and Zhang (2006)'s main finding that investment banks do not use affiliated mutual funds as "dumping ground" for unmarketable IPOs but further identify the inverse relationship between premarket demand and share allocated to affiliated mutual funds among purchased IPOs. Affiliated mutual funds are favored in a way that they can avoid cold IPOs but are not favored when it comes to allocations of hotter IPOs. Third, I provide more detailed analysis to the star-fund phenomenon. Although on average fund families engage in tactics that promote their top performers, different fund families exhibit large variation in terms of how they allocate IPO shares to their funds. Also, fund families appear to even out allocations among "star funds". Fourth, my study contributes to the IPO allocation literature. As Ritter and Welch (2002) point out, empirical papers in this literature focus on the difference between institutional and retail investors (Hanley and Wilhelm (1995), Aggarwal, Prabhala, and Puri (2002)). They call for future research on "...different classes and characteristics of institutional investors". My study fills this gap by examining allocations to affiliated mutual funds and unaffiliated mutual funds as distinct subgroups of institutional investors.

The amount of allocation to affiliated mutual funds may contain additional private information that is not reflected in the price adjustment during the bookbuilding. Benveniste and Spindt (1989)'s bookbuilding theory posits that investment banks allocate underpriced IPOs in exchange for investors to reveal private information. Hanley (1993) provides evidence that the final offer price only partially adjusts to new information, consistent with the bookbuilding theory. Following this line of thinking, Aggarwal, Prabhala, and Puri (2002) empirically show that allocations to institutional investors as a group contain private information not reflected in premarket demand and other public information. Although my allocation data is limited to affiliated mutual funds only, treating them as one type of institutional investor can test whether allocations to them contain additional private information. Contrary to Aggarwal et. al., the allocations to affiliated mutual funds as a group do not contain additional private information that can predict first-day IPO returns after controlling for premarket demand and other public information. While allocations to unaffiliated mutual funds as a group do predict first-day return. There are various explanations to the different results from affiliated and unaffiliated mutual funds. First, affiliated mutual funds may not receive the full share of allocation that they request for because of the crowding-out effect. Second, based on the *quid pro quo* explanation by Reuter (2006) that IPOs could be purchased with commission, investment banks are more likely to cuddle favor with unaffiliated fund families using IPO allocations, because affiliated mutual funds are unlikely to divert their transactions to broker-dealers other than their parent firms'.

The rest of the article is organized as follows. Section 2.2 introduces institutional background of the rules of law that governs the allocation of IPOs to affiliated mutual funds. Section 2.3 describes the data sources of the IPO sample and actual allocations, and the potential issues of using reported holdings as a proxy for actual allocations. Section 2.4 illustrates my empirical findings using IPO actual allocations. Section 2.5 compares results using quarter-end reported holdings. Section 2.6 examines whether IPO allocations contain private information. Section 2.7 concludes.

2.2 Institutional Background

2.2.1 SEC Rule 10f-(3)

The potential conflict of interest between the underwriting business and the fund management business of an investment bank has long concerned the Security and Exchange Commission (SEC). Section 10(f) of the Investment Company Act of 1940 barred affiliated mutual funds from buying shares of underwriting clients out of the fear of the investment banks dumping unmarketable shares to affiliated funds thus hurting the fund investors. The investment banks argued that shareholders of affiliated mutual funds should have the same access to client offerings as other investors. In 1958, the SEC adopted Rule 10(f)-3 to permit affiliated mutual funds to purchase securities from the syndicate if certain conditions are met. Those conditions include but not limited to: (1) purchases of securities do not exceed 3% of the offering (2) the purchase price is not more than the price paid by other purchasers (3) purchases must be made before the end of the first day on which any sales are made (4) purchases must be made from a syndicate member other than the affiliated member (5) a fund must report any such purchases on Form N-SAR detailing the terms of the transaction, from whom the securities are acquired, and the identity of the underwriting syndicate's members. In 1979, the SEC raised the limit of 3% to 4%. In 1997, the SEC again raised the limit to 25% and it remains as of now.

2.2.2 Mutual Fund Affiliation with Investment Bank

Affiliation between a fund management company and an investment bank could take a direct and an indirect form. A direct affiliation could be that a fund management company and an underwriting business belong to the same bank holding company. For example, J.P. Morgan Investment Management Inc. and J.P. Morgan Securities LLC belong to the same holding company JPMorgan Chase & Co. An indirect affiliation takes the form that the fund management company is only affiliated with the investment bank through its subadvisers. Subadvised mutual funds are not a rare breed in the fund industry. Majority of the mutual funds sponsored by large life insurance companies outsource portions of their portfolio decisions to advisers affiliated with investment banks. There is a third form of affiliation that is in between the direct and indirect affiliation. A bank holding company could grow its fund management business either through internal cultivation or through external acquisition. American Century Investment Management Inc was partially acquired by JPMorgan in 1999 and operated under its own brand name. Although it was minority-controlled by JPMorgan it still needs to disclose any IPO purchases that JPMorgan participates as a syndicate member. Appendix B lists the affiliation between an investment bank and its fund management business.

2.3 Data Sample and Summary Statistics

2.3.1 Data Sources

The IPO sample spans 2008 to 2014 and comes from the Thomson Financial Security Data Company (SDC) global new issues database. The reason I choose this sample period is because I am more interested in whether conflict of interest will be exacerbated during crisis times, as in and after the Great Recession. Following the IPO literature, I exclude unit offerings, American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), closed-end funds, limited partnerships (LPs), depository institutions, and Savings & Loans (S&Ls). I restrict my IPO sample to stocks that are listed on AMEX, Nasdaq, and NYSE. I also exclude IPOs that are not included in the Center for Research in Security Prices (CRSP) database. This results in a sample of 712 IPOs.

I compile affiliated mutual funds' IPO purchases and operational information from their N-SAR filings to the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Under the SEC's mandate, a registered investment company is required to file the N-SAR form twice a year, one is the NSAR-A form that covers a fund's first six fiscal months, and the second is the NSAR-B form that covers a fund's entire fiscal year. An N-SAR form is consisted of about 83 questions related to a fund's operations. Records of IPO purchases are not disclosed in the N-SAR form per se, instead they are recorded in an attached supplement file filed along with the N-SAR form. I download all N-SAR filings from 2008 to 2014, including all attachments and supplement files. A text-searching algorithm is employed to comb through all the downloaded filings to identify which ones contain IPO purchase records. I then hand-collect each IPO purchase in the filings identified. In each IPO purchase record, I collect the name of the issuer, the date of the issuance, the name of the fund purchasing the IPO, the number of shares and dollar amount purchased by the fund, the name of the adviser or subadviser of the fund, and the affiliation of the adviser or subadviser with the syndicate member. Between 2008 and 2014, there are total 4,540 disclosures of IPO purchases by affiliated mutual funds.

Fund characteristics comes from CRSP survivor-bias-free US mutual fund database. The fund characteristics I am interested in are fund name, TNA, age, and return history. Both CRSP mutual fund database and the CDA/Spectrum Mutual Funds Holdings database

(S12) provide holdings reported by mutual funds with the exception that CRSP mutual fund database offers coverage starting from 2001. Because the sample period is from 2008 to 2014, I use both databases to complement each other. Another advantage of using reported holdings from CRSP mutual fund database is that it updates holdings more frequently for some mutual funds that choose to report holdings in a higher frequency, such as monthly instead of quarterly. When it comes to use reported holding to proxy for actual allocation, the closer the two dates the more accurate the proxy.

2.3.2 IPO Sample and Allocations to Affiliated Mutual Funds

Table 2.1 shows the summary statistics of the IPO sample between 2008 and 2014. The total number of IPOs issued during this time period is 712 ($202 billion) after excluding unit offerings, American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), closed-end funds, limited partnerships (LPs), depository institutions, and Savings & Loans (S&Ls). The Great Recession from December 2007 to June 2009 may explain the low IPO activities in 2008 (22 IPOs) and 2009 (44 IPOs). Afterward, IPO activities started picking up gradually. When I run my analysis later I divide the time period into three sub-periods, 2008 to 2010, 2011 to 2012, and 2013 to 2014. This division intends to capture the period during the Great Recession, the period emerging from the crisis, and the period normalizing after the crisis. Because my interest is in IPOs allocated to affiliated mutual funds, I report in Panel B IPOs underwritten by affiliated investment banks that acted as lead- or co-manager in the syndicate. IPOs in which affiliated investment banks acted as selling member are excluded. This whittle down the number of IPOs to 508. Although the number of IPOs is reduced by almost 30%, the dollar volume tells a different story. The dollar amount underwritten by these investment banks represent 94% of the total dollar amount ($189 vs. $202 billion). Overa ll, IPOs underwritten by affiliated investment banks have higher pre-offer book asset, higher offering amount, higher price adjustment, and higher first-day return. I further divide the 508 IPOs into IPOs that were allocated to affiliated mutual funds and not allocated. More than half of the 508 IPOs (270 IPOs) were allocated to affiliated funds. On average, IPOs allocated to affiliated funds have higher pre-offer book asset ($4.1 billion), larger offering amount ($571 million), greater price adjustment (3.1%), and higher first-day return (21.25%).

Disclosures of IPO purchases by affiliated mutual funds are summarized in Table 2.2. Between 2008 and 2014, the total number of allocations is 3,302 after excluding allocations to closed-end funds and funds I am not able to match with CRSP mutual fund database. The number of allocations increases over the years following the same increasing trend of IPO activities. The average share of an IPO allocated to an affiliated fund is 0.27%, which is about 0.22% of the fund's TNA. The average TNA of a fund purchasing an IPO is about $888 million. And the first-day return contribution to the fund is around 3.55 bps. These numbers indicate that on average it is unlikely for an IPO to give a fund a large performance boost. In Panel B, I summarize allocations at the investment bank level. Appendix B lists the details of investment banks that have fund management business. An IPO is underwritten by a syndicate of investment banks. Since my study concerns only IPOs underwritten by affiliated investment banks acting as lead- or co-manager, I exclude allocations by affiliated investment banks acting as selling managers. This yields a total 463 allocations at the investment bank level. On average, an affiliated investment bank allocates 1.78% of an IPO to its affiliated mutual funds, out of 19.4% of shares allotted to the investment bank. So a little less than 10% of shares allotted is allocated to its affiliated fund business. For each affiliated investment bank, its mutual fund business manages about 54 equity mutual funds, with total AUM of around $58 billion. Underwriters usually do not allocate IPO shares directly to mutual fund, instead they allocate to fund family who then decide how to divide shares among individual funds. I thus calculate the percentage of IPO allocation to the fund family's total AUM. The percentage is around 0.03% considering that the average AUM is around $58 billion. Panel C summarize allocations to the stock level. On average, there are 3 affiliated investment banks co-managing an IPO issuance. They are allocated 59% of total shares offered. Combined their affiliated fund management business are allocated 2.93% of an IPO issuance. This is non-trivial share of allocation considering that IPOs are often oversubscribed.

2.3.3 Issues in Using Reported Holdings as Proxy for Actual Allocations

When it comes to the analysis of IPO allocations to mutual fund or institutional investors in general, limited access to allocation data is a big impediment to better understanding the allocation mechanism. To solve the data limitation problem, the literature rely on mandatory disclosure of mutual fund holdings as a proxy for actual allocations, or in the case for institutional investors the disclosure of holdings by institutional money managers managing more than $100 million worth of assets. For example, Ritter and Zhang (2007) use holding disclosure of affiliated mutual funds within 6 months of IPO issuance to identify whether fund is allocated IPO shares. Reuter (2006) uses mutual fund reported holdings as actual allocations to study favoritism. Both studies acknowledge the limitation of this approach and come up with ways to circumvent it. Ritter and Zhang (2007) use a dummy variable instead of allocation amount, arguing that aftermarket buying and selling would have minimum impact on the accuracy of dichotomous outcome. Reuter (2006) uses the subsample of IPOs whose offer date is right around the month end when mutual funds disclose their holdings to sharpen the test results.

Another issue of using reported holdings in Ritter and Zhang is that they likely omitted a portion of subadvised mutual funds. Ritter and Zhang uses the name of investment management company to identify mutual funds affiliated with investment banks. CRSP mutual fund database only report the name of the management company, or the name of the main advisor, even though the fund could be managed by more than one adviser. For example, Advanced Series Trust's AST Small Cap Value Portfolio is managed by AST Investment Services as the main adviser. JPMorgan serves as its subadviser and allocated 76 IPOs to it between 2010 and 2014, totaling $29 million. It is common that mutual funds sponsored by large insurance companies hire affiliated advisers to manage portions of its portfolio. Table 2.3 breaks down allocations by what role affiliated adviser serves. Panel A shows allocations to funds of which affiliated adviser serves as main adviser. Panel B shows allocations to funds of which affiliated adviser serves as subadviser. Almost one third of IPO allocations by count goes to funds sub-advised by affiliated advisers. On average, a main-advised fund receives larger share of IPO allocation (0.34%) compared to a sub-advised fund (0.11%). But this could be explained by the larger size of a main-advised fund compared to a sub-advised fund ($1,027 mil vs $600 mil). Also subadviser only manages a portion of the fund portfolio, which could be another reason that sub-advised fund receives a smaller share of IPO allocation. Because fund does not disclose the size of the subadvised portion, I cannot examine whether main-advised fund does receive a larger share of IPO allocation than sub-advised fund.

To gauge the applicability of proxying actual allocation using fund reported holdings, I test the correlation between my actual allocation data of affiliated mutual funds and their subsequent reported holdings within 6 months. I first compile all mutual funds affiliated with the list of investment banks in Appendix B regardless whether they are allocated IPOs or not. My sample of affiliated mutual funds that were actually allocated IPOs is a subset of this population. I then match the population of affiliated mutual funds with both CRSP mutual fund holdings database and S12 holdings database to identify holdings of the 508 IPOs underwritten by affiliated investment banks within 6 months of issuance. Table 2.4 summarizes the differences between actual allocation and reported holdings. I aggregate fund level allocation to stock level for ease of comparison. Out of the 508 IPOs, 233 were both allocated and later reported in fund holdings disclosure. Reported holdings these 233 IPOs are on average 0.51% higher than actual allocations. An interesting finding is that affiliated mutual funds bought 35 IPOs that were not allocated. These IPOs would be considered relatively cold IPOs, with lower premarket demand (-6.61%), and lower first-day return (9.76%). Affiliated mutual funds also liquidated 34 IPOs that were initially allocated. These group of IPOs are relatively hot IPOs, with higher premarket demand (4.82%), and higher first-day return (30.18%), indicating profit-taking behavior. I graph the change of actual allocation to reported holdings at the fund level in Figure 2.2. I divide the affiliated mutual funds into two groups, one that purchased IPOs of positive first-day return, the other that purchased IPOs of negative first-day return. Within 6 months of IPO purchase, more than 30% of the group of funds that purchased positive first-day return IPOs liquidated their positions, compared to more than 10% of the group of funds that purchased negative first-day return IPOs. The same pattern of liquidating positive first-day return IPOs shows up in the sample of funds that reported holdings within 30 days of IPO issuance.

I also calculate the Pearson correlation coefficient between actual allocations and reported holdings. The number is 0.60 (p=0.0001), in line with what is reported by Hanley and Wilhelm (1995) and Ritter and Zhang (2007), indicating it is a viable alternative to using actual allocation (Hanley and Wilhelm (1995)). I further repeat my regression using reported holdings and compare it to regression using actual allocation. I find that regression using reported holdings underestimate the coefficients of interest. This confirms the concern raised by Reuter (2006). My comparison of actual allocations and reported holdings is the largest in scale in the literature. Hanley and Wilhem (1995) compare actual allocations and reported holdings of 38 IPOs, Ritter and Zhang (2007) 11 IPOs. By comparison, my study uses a sample of 508 out of 712 IPOs underwritten between 2008 and 2014. Although the number of investment banks with fund management business involved in the 508 IPOs is only eleven, the IPOs they participated as lead- or co-manager account for 94% of the total offering amount ($189 billion vs. $202 billion) and 93% of the amount of money left on the table ($26 billion vs. $28 billion). The scope of my sample captures the economic significance of IPO underpricing. The results of the comparison would serve a guideline in future researches where reported holdings have to substitute for actual allocations.

2.4 Empirical Findings Using Actual Allocations

2.4.1 IPO Purchase Decision and Percentage Allocation

In this section, I empirically test what factors influence affiliated mutual funds to purchase an IPO and what influence the share percentage allocated to them.

Ritter and Zhang (2007) use a dummy variable method to test the “dumping ground” hypothesis and the nepotism hypothesis. The dummy variable, IPO purchase decision, is 1 if an affiliated mutual fund reported holdings of an IPO within 6 months of issuance and 0 otherwise. This method mitigates the potential discrepancy of misidentifying IPO allocation due to aftermarket trading. The dummy variable method hinges on an important assumption, that institutional investors are unlikely to liquidate their entire IPO allocations and they are unlikely to purchase aftermarket an IPO that was not allocated to them at the first place. But the dummy variable method would not be able to answer the question of how much share percentage of an IPO is allocated to affiliated mutual funds and what determines the percentage allocation. I set to answer these questions using the actual allocation data. With the fund-level allocation data, I am able to aggregate it to investment bank level so I can study the average behavior of different investment banks in terms of their allocation decisions regarding affiliated mutual funds. Later I will repeat the same analysis on subsamples of different investment banks to test whether there is heterogeneity among investment banks in terms of their IPO allocation practices.

I first replicate Ritter and Zhang’s findings using their dummy variable method. For purchase decision, I want to test the joint hypothesis that whether investment banks use affiliated mutual funds as “dumping ground” for unmarketable IPOs and whether affiliated mutual funds take advantage of private information produced during the bookbuilding to avoid relatively cold IPOs. Univariate analysis shows that IPOs allocated to affiliated mutual funds have higher premarket demand and higher first-day return but that is without controlling for other covariates that may influence funds' purchase decision. I run the following probit model to identify the determinants of affiliated mutual funds' decision to purchase an IPO.

$$\begin{aligned} PurchaseDummy = \lambda Adjustment + \beta_1 Ln(Asset) + \beta_2 LeadRank \\ + \beta_3 TechDummy + \beta_4 PctAllotment \\ + \beta_5 OverAllotmentDummy + \beta_6 LeadManagerDummy + \beta_7 Ln(AUM) \end{aligned} \tag{1}$$

The dependent variable $PurchaseDummy$ is a dummy variable of 1 if the IPO is purchased by affiliated mutual funds as a group, and 0 otherwise. $Adjustment$ is the premarket price adjustment calculated as $(\frac{\text{offer price} - \text{mid-point of filing price}}{\text{mid-point of filing price}})$. Hanley (1993) shows that if the offer price is at the upper end of the initial filing price range, the IPO is in higher premarket demand and its underpricing will be more severe. If affiliated mutual funds choose IPOs with higher premarket demand, they are likely taking advantage of private information produced during the bookbuilding and unlikely to be used as "dumping ground" by investment banks. $Ln(Asset)$ is the natural-logarithm of the issuer's pre-offer book value of assets. $LeadRank$ is the reputation rank of the lead- or co-manager of the IPO.[11] I take the average of the reputation ranks of investment banks if there are more than one lead- or co-manager involved in the IPO. $TechDummy$ is 1 if the IPO issuer is a technology company, and 0 oth-

[11] Reputation ranks are compiled by Jay Ritter and published on his website.

erwise.[12] $PctAllotment$ is the percentage of shares allotted to affiliated investment banks in the syndicate. I want to test whether it is more likely that affiliated mutual funds purchase an IPO if affiliated investment banks are allotted more shares. $OverAllotmentDummy$ is 1 if lead managers exercise the overallotment option aftermarket. It is common for the investment banks to sell up to 115 percent of the issue at the offering and create a naked short position. If aftermarket the stock price goes up, an investment bank can exercise the overallotment option to cover the naked short position. If the stock price goes down, then the investment bank is forced to buy back the oversold portion of the IPO shares. Overallotment is usually an indication of high premarket demand. $LeadManagerDummy$ is 1 if the investment bank acts as lead manager in the syndicate and 0 if co-manager. $Ln(AUM)$ is the natural log of total asset under management of the affiliated mutual fund adviser. In equation (1), the parameter of interest is λ. If $\lambda > 0$, the decision to purchase an IPO is closely related to the affiliated investment bank's private information about premarket demand. In a separate but related regression setup, I replace the explanatory variable $Adjustment$ with $1stDayRet$ to test the relation between IPO purchase decision and IPO's first-day performance.

Table 2.6 Column [1] summarizes the results for regression equation (1). The results show a strong correlation between premarket demand and purchase decision after controlling for other variables that likely influence affiliated mutual funds' purchase of an IPO. A 10% increase in premarket demand will increase the probability of purchasing the IPO by 0.1. An issuer's pre-IPO book asset value also has a positive effect on funds' purchase decision. Affiliated mutual funds are more likely to purchase IPOs of larger issuers in terms of

[12]Detailed identification of Tech IPOs could be found on Jay Ritter's website.

book assets. After controlling for other covariates, whether an IPO is technology related also significantly influence affiliated mutual funds' decision to purchase an IPO. Interestingly, the more IPO shares alloted to affiliated investment banks, the less likely affiliated mutual funds will purchase that IPO. The regression shows similar results if I replace $Adjustment$ with $1stDayRet$, although the effect of $1stDayRet$ on the decision to purchase an IPO is weaker compared to $Adjustment$.

For percentage allocation by affiliated investment banks to their affiliated mutual funds, I run the following OLS regression to test the relation between premarket demand and the percentage allocation of an IPO.

$$\begin{aligned} PctAllocation = \lambda Adjustment + \beta_1 Ln(Asset) + \beta_2 LeadRank \\ + \beta_3 TechDummy + \beta_4 PctAllotment \\ + \beta_5 OverAllotmentDummy + \beta_6 LeadManagerDummy + \beta_7 Ln(AUM) \end{aligned} \tag{2}$$

The dependent variable $PctAllocation$ is the percentage share of an IPO allocated to affiliated mutual funds. The explanatory variables are the same as in regression equation (1). To test whether there is a crowded-out effect when an IPO has high premarket demand, I study the sign and magnitude of λ after controlling for other covariates that may also influence the allocation decision.

Table 2.6 Column [2] shows that at the average investment bank level, the greater the premarket demand, the lower allocation to its affiliated mutual funds. A 10% increase in price adjustment results in a 3.6% decrease in allocation. Also, the larger the pre-IPO book asset value, the lower allocation to affiliated mutual funds. Surprisingly, the equity AUM of the adviser affiliated with the investment bank has no significant relationship with the share of allocation. If an investment bank allocates IPO shares proportional to AUM, then I would expect to see a positive relationship. One explanation to this is that typically IPO allocations to an affiliated adviser is tiny compared to its total asset under management, which often is in the scale of tens of billions (Appendix B).

It is now clear that although affiliated mutual funds take advantage of the private information during the bookbuilding process to purchase only IPOs with higher premarket demand, the percentage allocation is inverse to the hotness of these IPOs. So whether these allocations give them performance boost is an empirical question. I devise a variable, $PerfBoost$, to measure the first-day return contribution (in bps) from the percentage allocation of an IPO. I run the following OLS regression to test the relation between return contribution and premarket demand of an IPO.

$$\begin{aligned} PerfBoost &= \lambda Adjustment + \beta_1 Ln(Asset) + \beta_2 LeadRank \\ &+ \beta_3 TechDummy + \beta_4 PctAllotment \\ &+ \beta_5 OverAllotmentDummy + \beta_6 LeadManagerDummy + \beta_7 Ln(AUM) \end{aligned} \tag{3}$$

Table 2.6 Column [3] shows that after controlling for other covariates, premarket demand has no significant relation with first-day return contribution. But IPOs of issuers with higher book value as well as of tech companies are more likely to give positive performance boost to the fund in the first day of trading.

2.4.2 IPO Purchase Decision and Percentage Allocation: Sub-Sample Analysis

The sample period from 2008 to 2014 cover the period during the Great Recession, which had relatively low IPO activities in 2008 and 2009. It would be interesting to test whether IPO allocations to affiliated mutual funds during low volume years differ from during relatively high volume years. I repeat the regression analysis of regression equation (1), (2), and (3) in sub-samples divided by three sub-periods, 2008-2010, 2011-2012, and 2013-2014. The sub-period 2008-2010 represents the period with relatively low IPO activities. Table 2.7 Panel A shows that during all three sub-periods, the IPO purchase decision is positively correlated with premarket demand. But Panel B shows that during low volume years (2008-2010) the inverse relation between percentage allocation and premarket demand is more pronounced compared to high volume years later.

The investment bank level analysis only provides insight of the average behavior by different investment banks. Though most of the eleven investment banks covered in this study are large Wall Street investment banks, some of them are dominating enough in the underwriting business that one has to question whether the average behavior is a reflection of these dominating banks, or there could large variation in terms of different allocation practices employed by these investment banks. I thus repeat regression equation (1), (2) and (3) for each investment bank. For investment banks that have few allocations, I aggregate them together into one group.

Table 2.8 shows the allocation decision by the top 5 investment banks by IPO allocations, JPMorgan (JPM), Goldman Sachs (GS), Morgan Stanley (MS), Wells Fargo (WF), Deutsche Bank (DB), and the rest (Other). Other than WF showing a positive but insignificant relationship between premarket demand and its allocation, all other investment banks follow the same pattern of allocating less share of an IPO when it is in higher premarket demand. So the average effect among investment banks demonstrated earlier is not dominated by any single investment bank but reflects a systemic practice among most investment banks.

2.4.3 Within-Fund Family IPO Purchase and Percentage Allocation

So far, I have examined the determinants of IPO purchase decision by affiliated mutual funds and the determinants of percentage allocation by affiliated investment banks. How fund advisers allocate IPO shares among their individual funds within fund families is an unanswered question. Recent development in the mutual fund literature has started paying attention to the so-called “star fund” phenomenon. Mutual funds within the family that charge higher expense and/or have better past performance are designated as “star funds” and often receive preferential treatment by the management company. Gasper, Massa and Matos (2006) is the first study to examine how fund family allocate IPO shares to their individual funds. Using reported holdings as proxy for actual allocations, they find that fund family does favor “star funds”, funds that charge higher fees and/or have better past performance. My method is different from theirs. I first estimate the probability of a fund within a fund family receiving IPO allocation. Given that the sample of allocated IPOs is already relatively hot compared to the sample of unallocated ones, and if the star fund hypothesis is true, a fund receiving IPO allocations should exhibit the typical attributes of a star fund. Among those funds that are allocated IPO shares, I then examine the fund attributes that drive the percentage allocation. So for the first step, I run the following probit regression to test the determinants of a fund receiving IPO allocations.

$$\begin{aligned} PurchaseDummy = \beta_1 Adjustment + \beta_2 ExpenseRatio + \beta_3 PastAlpha \\ + \beta_4 Ln(TNA) + \beta_5 Ln(Age) \\ + \lambda_1 ExpenseRatio * Adjustment + \lambda_2 PastAlpha * Adjustment \\ + \lambda_3 Ln(TNA) * Adjustment + \lambda_4 * Ln(Age) * Adjustment \end{aligned} \tag{4}$$

$PurchaseDummy$ is a dummy variable of 1 if the fund within the fund family is allocated IPO shares. $ExpenseRatio$ is the annual expense fee the fund charges. $PastAlpha$ is the intercept from regressing the fund's past 24-month net returns on Fama-French-Carhart four factors. $Ln(TNA)$ is the natural-logarithm of the fund's TNA prior to the IPO issuance. $Ln(Age)$ is the natural-logarithm of the fund's age in month. If the fund has multiple share classes, age is calculated using the oldest share class. I interact $Adjustment$ with $ExpenseRatio$, $PastAlpha$, $Ln(TNA)$, and $Ln(Age)$ to study any incremental effect. The parameters of interest are $ExpenseRatio$ and $PastAlpha$. If the star fund hypothesis is true, the coefficients of both parameters should be positive and significant.

In Table 2.9 Column [1], consistent with the star fund hypothesis, funds with higher expense ratio are more likely to be allocated IPO shares. Although the coefficient of $PastAlpha$ is positive, it is insignificant, calling into question the hypothesis that better performing funds are more likely to receive IPO allocations. Fund TNA does not appear to be a determinant of IPO allocation, while fund age does. Older funds are more likely to be allocated IPO shares.

Conditional on receiving IPO allocations, I examine the determinants of percentage allocation to individual funds. I run the following OLS regression.

$$\begin{aligned} PctAllocation = \beta_1 Adjustment + \beta_2 ExpenseRatio + \beta_3 PastAlpha \\ +\beta_4 Ln(TNA) + \beta_5 Ln(Age) \\ +\lambda_1 ExpenseRatio * Adjustment + \lambda_2 PastAlpha * Adjustment \\ +\lambda_3 Ln(TNA) * Adjustment + \lambda_4 * Ln(Age) * Adjustment \end{aligned} \tag{5}$$

The dependent variable $PctAllocation$ is the percentage allocation to an individual fund. All the explanatory variables are the same as in regression equation (4).

The results in Table 2.9 Column [2] shows an interesting pattern. The coefficients on $ExpenseRatio$, $PastAlpha$, $Ln(TNA)$, and $Ln(Age)$ are all positively significant, but the coefficients on the interaction terms involving $ExpenseRatio$, $PastAlpha$, and $Ln(TNA)$ are all negatively significant. So a more expensive fund received smaller allocation of hotter IPOs but larger allocation of colder ones. Similar explanation applies to better-performing and larger funds. This is contrary to Gaspar et. al. (2006)'s findings that "star funds" receive more shares of hotter IPOs. The different outcomes could be due to different samples as they use the entire mutual fund sample while I use only the affiliated mutual fund sample.

Table 2.10 shows that separate regressions for individual fund adviser show similar patterns to pooled regression although J.P.Morgan seems to dominate the sample inferences due to its large presence. Affiliated fund advisers in general appear to even out the allocation among the "star funds" that they choose to receive IPO allocations.

2.5 IPO Purchase Decision and Percentage Allocation Using Reported Holdings

Since prior literature on IPO allocations to affiliated mutual funds use quarter-end reported holdings to proxy for actual allocations, and we have already seen in Table 2.4 that affiliated mutual funds tend to reduce holdings of hotter IPOs and increase holdings of colder ones aftermarket, it will be helpful to measure the impact of such discrepancies on inferences of the inverse relation between premarket demand and percentage allocation. Following Ritter and Zhang (2007), I compile the nearest quarter-end reported holdings of IPOs for investment bank-affiliated mutual funds. I identify affiliated mutual funds based on their fund names as well as the affiliation of their main adviser to major IPO underwriters. I conduct the analysis at two sample levels. One is at the IPO stock level, following Ritter and Zhang (2007). Another is at the fund level, following Gaspar et. al. (2006).

Table 2.11 shows the results at the IPO stock level, using both actual allocations and reported holdings. For the probit regression using $PurchaseDummy$ as dependent variable, both samples of actual allocations and reported holdings show similar inferences on the relation between premarket demand and likelihood of purchasing an IPO. That is, the hotter the IPO, the more likely it will be purchased by affiliated mutual funds. But the coefficient on $Adjustment$ using reported holdings (0.028) is smaller than the same coefficient using actual allocations (0.039). For the OLS regression using $PctAllocation$ as dependent variable, although both samples infer an inverse relation between premarket demand and percentage allocation, the coefficient on $Adjustment$ using reported holdings (-0.003) is not statistically significant. While the same coefficient using actual allocations (-0.028) is statistically significant. The discrepancy between the inferences confirm the evidences shown in Table 2.4 that due to aftermarket selling of hotter IPOs and buying of colder IPOs, the inferences of the relation between premarket demand and percentage allocations will be underestimated.

I then repeat the same analysis of within-fund family purchase decision and percentage allocation using reported holdings. Due to higher granularity of the sample, the differences of inferences are more pronounced here. For example, in Table 2.12 Column [1], the coefficient on $Adjustment$ is a negatively significant -0.024, as opposed to a negatively insignificant -0.018 in Table 2.9 Column [1]. Also in Table 2.12 Column [1], the coefficient on $ExpenseRatio$ is no longer positively significant as in Table 2.9 Column [1], which indicates that higher-expense affiliated mutual funds are no more likely to receive IPO allocations than lower-expense ones.

The takeaway from this comparison between using actual allocations and reported holdings is that at a coarser sample level the sign of the coefficient are likely to hold although it will be underestimated. But at a finer sample level, the inferences are likely to be called into question.

2.6 Does IPO Allocation Contain Private Information?

In their seminal study on IPO allocations, Aggarwal, Prabhala, and Puri (2002) shows that institutional investors are favored at the cost of retail investors. The more in demand an IPO is the higher percentage allocation institutional investors as a group receive. Affiliated mutual funds is one type of institutional investors and there are other types, such as unaffiliated mutual funds, hedge funds and pension funds, etc. My finding shows that although affiliated mutual funds as a group avoid cold IPOs, their allocations of relatively hot IPOs are in contrary to Aggarwal et. al. (2002)'s findings. If affiliated mutual funds receive less share of oversubscribed IPOs as the inverse relationship between premarket demand and allocation shows, either other types of institutional investors or retail investors as a group must receive more share of oversubscribed IPOs.[13] I do not have the data of allocations to investors other than affiliated mutual funds so a direct comparison is impossible. But one group of institutional investors, unaffiliated mutual funds, may provide an indirect comparison. I follow the literature and use the quarter-end holdings of unaffiliated mutual funds within 6 months of IPO issuance to proxy for actual allocations. Table 2.5 shows the IPOs allocated to unaffiliated mutual funds. Of the 508 IPOs underwritten by investment banks with fund management business, 496 were allocated to unaffiliated mutual funds. Among the group of IPOs that are allocated to affiliated mutual funds (270 IPOs), 266 are allocated to unaffiliated mutual funds. Among the group of IPOs that are not allocated to affiliated mutual funds (238 IPOs), 230 are allocated to unaffiliated mutual funds. So it does not appear that unaffiliated mutual funds as a group are avoiding cold IPOs entirely, although the share of allocation is smaller (25.32% vs. 31.69%). I am not particularly interested in the aggregated share of allocation because unaffiliated mutual funds as a group is larger both in number and scale than affiliated mutual funds as a group. I am more interested in whether there also exists an inverse relationship between premarket demand and share of allocation to unaffiliated mutual funds as a group, similar to what is observed for affiliated mutual funds.

[13] Numerus studies have shown that institutional investors as a group are favored in the IPO allocation process.

I test the relationship between IPOs' premarket demand and their allocations to unaffiliated mutual funds as a group using the same regression setup as in regression equation (2). I run three separate OLS regressions using the whole sample (482 IPOs), the allocated sample (266 IPOs), and the unallocated sample (230 IPOs). Table 2.13 shows the regression results. In Panel A, other than the period from 2008 to 2010, all other periods show a positive relationship between premarket demand and share of allocation to unaffiliated mutual funds as a group. This is consistent to the findings in Aggarwal et. al. (2002) that institutional investors as a group receive more percentage allocation of hotter IPOs. In Panel B, contrary to the inverse relationship from the test using affiliated mutual funds, unaffiliated mutual funds as a group is allocated more share of oversubscribed IPOs. A 10% increase in price adjustment results in a 1.69% increase in allocation. The magnitude of increase in allocation to unaffiliated mutual funds as a group is not of interest here because both the number and asset under management (AUMs) of unaffiliated mutual funds are larger than affiliated mutual funds as a group. What is more telling is the positive relationship for unaffiliated mutual funds between the premarket demand of IPOs and their allocation to them as a group.

Next I examine whether IPO allocations to affiliated mutual funds as a group contain private information on first-day return in addition to other variables, such as premarket price adjustment. Aggarwal et. al. (2002) find that allocations to institutional investors as a group contain additional information that predicts first-day return. Their evidence supports both the bookbuilding theory (Hanley and Wilhelm (1995)) and the "Lemon" model of Rock (1986). Institutional investors reveal private information to investment banks to help them reduce underpricing and as a return they receive favorable allocations. But they do not fully reveal their information so they can profit from any remaining underpricing. Although affiliated mutual funds is only a special type of institutional investors, it will be interesting to test whether allocations to them contains additional private information to predict first-day returns. I run the following OLS regression to test this hypothesis.

$$\begin{aligned} FirstDayReturn = \gamma PctAllocation + \lambda Adjustment + \beta_1 Ln(Asset) + \beta_2 LeadRank \\ + \beta_3 TechDummy + \beta_4 PctAllotment + \beta_5 OverAllotmentDummy \end{aligned} \tag{6}$$

The dependent variable $FirstDayReturn$ is the percentage change from IPO offer price to its first-day closing price. The parameter of interest is γ. If indeed as the bookbuilding theory and the "Lemon" model predict, γ would be positive and significant after controlling for other covariates that predict first-day returns.

The results in Table 2.14 tell a different story. In contrary to Aggarwal et. al. (2002), allocations to affiliated mutual funds as a group do not contain private information to predict first-day return after controlling for other covariates. The coefficient of $Allocation$, γ, is only significant in the period between 2008 and 2010, but the sign is negative. The result is also consistent with Hanley (1993) that price adjustment has significant predictive power in explaining the variation of first-day return. A 10% increase in $Adjustment$ corresponds to a 7% increase in first-day return after controlling for other covariates. An issuer's pre-IPO book asset value has a negative correlation with its first-day return, indicating that smaller issuer is more likely to be underpriced. The positively significant coefficient on $OverAllotmentDummy$ indicates that IPO issues that are over-sold by investment banks tend to have higher first-day returns.

A natural follow-up test is to examine whether allocation to unaffiliated mutual funds as a group contain private information that can predict first-day return after controlling premarket demand. Aggarwal et. al. (2002) shows that institutional investors as a group do not reveal private information fully during the bookbuilding so their allocation predicts first-day return after controlling for premarket demand. Table 2.13 shows the regression results for three different samples. In Panel A, allocations to unaffiliated mutual funds as a group contain private information that predicts first-day return after controlling for premarket demand, thus consistent with Aggarwal et. al. (2002). The other two samples are largely consistent with this hypothesis too, except for certain time periods. Overall, unaffiliated mutual funds as a group is more similar to the type of institutional investors in Aggarwal et. al. (2002).

2.7 Conclusion

Using a novel hand-collected dataset of IPO allocations to affiliated mutual funds, I document that by being close to investment banks, affiliated mutual funds as a group take advantage of the private information produced during the bookbuilding. They successfully avoid relatively cold IPOs but appear to be crowded out by other investors in allocation of hot IPOs. Affiliated mutual funds as a type of institutional investor is distinct from institutional investors depicted in Aggarwal et. al. (2002) where they are allocated more share of hotter IPOs. An indirect comparison with unaffiliated mutual funds confirms this distinction. IPO allocation patterns to unaffiliated mutual funds as a group is more close to what is documented in Aggarwal et. al. (2002). Overall, affiliated mutual funds seem to carry a special status when it comes to IPO allocations.

Appendix A: Variable Definition

Variable name	Variable definition
Adjustment	Partial price adjustment as defined in Hanley (1993), calculated as $(\frac{\text{offer price} - \text{mid-point of filing price}}{\text{mid-point of filing price}})$.
FirstDayReturn	A measure of degree of underpricing of an IPO, calculated as $(\frac{\text{1st day closing price} - \text{offer price}}{\text{offer price}})$
Ln(Asset)	Natural-logarithm of an issuer's pre-IPO book asset value
LeadRank	Lead rank measures the prestige status of an investment bank, as defined in Carter and Manaster (1990). It is from Jay Ritter's website.
LeadManagerDummy	A dummy variable of 1 if an investment bank is one of the lead-managers in the syndicate, 0 if the investment bank is one of the co-managers
TechDummy	A dummy variable of 1 if an IPO is technology related, 0 otherwise. Ritter and Zhang (2007) define Tech IPO as those with Standard Industrial Classification (SIC) codes of 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371, 7372, 7373, 7374, 7375, 7378, and 7379. Additional Tech IPOs, such as internet companies, are compiled on Jay Ritter's website.
OverAllotmentDummy	A dummy variable of 1 if the IPO is over-allocated to investors. Typically the lead manager will over-allocate 15 % of the issue.
Ln(TNA)	Natural-logarithm of a mutual fund's Total Net Assets (TNA) reported at the end of the month prior to IPO issuance
Ln(AUM)	Natural-logarithm of the asset under management (AUM) of mutual fund advisers affiliated with investment banks
ExpenseRatio	Annual expense fee charged by a mutual fund
PastAlpha	The intercept from regressing a mutual fund's past 24-month net returns on Fama-French-Carhart four factors
Ln(Age)	Natural-logarithm of a mutual fund's age in months. For funds with multiple share classes, age is calculated using the oldest share class.

Appendix B: Investment Banks and Affiliated Advisers

Investment bank	Affiliated adviser	Invest-ment bank lead rank	IPO allocated	Number of equity mutual funds	Equity funds asset under manage-ment ($ in mil.)
J.P. Morgan Securities Inc	J.P. Morgan Asset Management American Century Investment Management (divested in 2011)	9.001	239	57	169,442
Morgan Stanley & Co	Morgan Stanley Investment Management Van Kampen Investments Inc (divested)	9.001	226	24	19,830
Goldman Sachs & Co	Goldman Sachs Asset Management	9.001	213	46	73,339
Deutsche Bank Securities Inc	Deutsche Asset Management	8.501	176	30	24,234
Wells Fargo Securities LLC (including Wachovia)	Wells Capital Management Evergreen Investments	8.001	136	50	62,990
UBS Securities Inc	UBS Global Asset Management	8.501	103	17	6,447
Raymond James & Associates Inc	Eagle Asset Management	7.001	95	6	5,357
Bank of America Merrill Lynch (including Banc of America Securities LLC and Merrill Lynch Pierce Fenner & Smith)	Columbia Management Company (divested) Blackrock Inc (divested in 2011)	8.501	82	147	263,367
Jefferies & Co Inc	MassMutual	8.001	39	46	23,726
Sanford C Bernstein & Co Inc	AllianceBernstein	8.001	11	47	23,658
Bank of New York Capital Markets Ltd	BNY Mellon Investment Management (including Dreyfus)	8.001	3	38	22,166

Table 2.1: IPOs Issued between 2008 and 2014

The table summarizes IPOs issued between 2008 and 2014. Panel A shows summary statistics of all IPOs, excluding unit offerings, American Depository Receipts (ADRs) , Real Estate Investment Trusts (REITs), closed-end funds, limited partnerships (LPs), depository institutions, and Savings & Loans (S&Ls). Panel B shows summary statistics of IPOs underwritten by affiliated investment banks acting as lead- or co-managers whose asset management subsidiaries manage mutual funds (affiliated mutual funds). Panel C shows summary statistics of IPOs that were underwritten by affiliated investment banks and allocated to affiliated mutual funds. Panel D shows summary statistics of IPOs that were underwritten by affiliated investment banks but not allocated to affiliated mutual funds. Total offering is the aggregate dollar amount of all IPO offerings during the sample period. Money left on the table measures the degree of IPO underpricing in aggregate dollar amount. Price adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. Pre-IPO book asset is the reported book value of the IPO issuer. Hi-Tech IPO is defined as in Ritter and Zhang (2007).

	2008-2014	2008	2009	2010	2011	2012	2013	2014
Panel A: All IPOs								
Number of IPOs	712	22	44	90	82	92	164	218
Total offering ($ in mil.)	202,016	22,816	12,719	29,307	26,324	31,027	37,392	42,432
Mean offering ($ in mil.)	284	1,037	289	326	321	337	228	195
Median offering ($ in mil.)	102	135	140	100	148	93	103	92
Money left on the table ($ in mil.)	27,979	5,610	1,436	1,689	3,495	2,780	7,623	5,345
Number excersized overallotment options	512	9	26	62	59	69	135	152
Mean 1st day return (%)	14.94	5.09	9.56	9.16	13.84	17.66	19.51	15.24
Median 1st day return (%)	6.67	-1.46	5.65	2.38	6.36	11.01	11.44	5.18
Mean price adjustment (%)	-3.65	-6.03	-1.55	-7.77	0.73	-2.48	-1.40	-5.97
Median price adjustment (%)	0.00	-4.38	0.00	-6.00	0.00	0.00	0.00	0.00
Mean pre-IPO book asset ($ in mil.)	1,854	1,069	968	2,380	1,492	988	2,440	1,957
Median pre-IPO book asset ($ in mil.)	126	274	397	152	176	133	108	74
% of Hi-Tech IPOs	28.93	18.18	29.55	27.78	42.68	39.13	25.00	23.85
Panel B: IPOs underwritten by investment banks with affiliated mutual funds								
Number of IPOs	508	17	38	70	64	73	113	133
Total offering ($ in mil.)	189,315	22,533	12,488	28,243	25,239	29,848	34,037	36,927
Mean offering ($ in mil.)	373	1,325	329	403	394	409	301	278
Median offering ($ in mil.)	141	188	155	140	170	114	167	125
Money left on the table ($ in mil.)	26,067	5,595	1,449	1,632	3,422	2,598	6,997	4,375
Number excersized overallotment options	388	7	26	52	52	55	97	99
Mean 1st day return (%)	16.45	5.38	11.29	9.93	15.92	19.08	22.36	16.55
Median 1st day return (%)	9.03	-1.25	6.67	2.95	8.98	12.50	13.52	8.07
Mean price adjustment (%)	-2.14	-3.51	-1.40	-7.49	3.42	-0.60	-0.34	-4.40
Median price adjustment (%)	0.00	-4.00	0.00	-5.88	5.41	0.00	0.00	0.00
Mean pre-IPO book asset ($ in mil.)	2,516	1,367	1,110	3,039	1,880	1,215	3,333	3,115
Median pre-IPO book asset ($ in mil.)	242	408	562	205	363	192	252	206
% of Hi-Tech IPOs	32.87	17.65	28.95	31.43	42.19	41.10	29.20	30.83
Panel C: IPOs allocated to affiliated mutual funds								
Number of IPOs	270	7	27	35	31	36	62	72
Total offering ($ in mil.)	154,118	21,343	10,411	22,550	19,382	24,919	26,831	28,681
Mean offering ($ in mil.)	571	3,049	386	644	625	692	433	398
Median offering ($ in mil.)	219	500	279	167	315	170	236	175
Money left on the table ($ in mil.)	23,090	5,660	1,426	1,479	2,957	2,084	6,005	3,480
Number excersized overallotment options	222	5	22	28	25	28	55	59
Mean 1st day return (%)	21.25	17.43	15.38	15.07	21.67	22.77	27.38	20.61
Median 1st day return (%)	12.66	16.67	10.13	6.29	8.88	15.05	18.48	11.38
Mean price adjustment (%)	3.10	1.70	2.30	-2.70	8.69	6.76	3.92	1.41
Median price adjustment (%)	5.56	0.00	6.67	0.00	9.52	6.97	6.78	1.28
Mean pre-IPO book asset ($ in mil.)	4,066	2,727	1,272	5,453	3,300	1,336	5,447	5,075
Median pre-IPO book asset ($ in mil.)	462	743	622	222	492	218	677	319
% of Hi-Tech IPOs	35.56	14.29	37.04	31.43	38.71	44.44	29.03	38.89
Panel D: IPOs not allocated to affiliated mutual funds								
Number of IPOs	238	10	11	35	33	37	51	61
Total offering ($ in mil.)	35,197	1,189	2,077	5,693	5,857	4,930	7,206	8,245
Mean offering ($ in mil.)	148	119	189	163	177	133	141	135
Median offering ($ in mil.)	100	126	103	90	133	86	96	101
Money left on the table ($ in mil.)	2,978	(65)	23	153	466	514	992	895
Number excersized overallotment options	166	2	4	24	27	27	42	40
Mean 1st day return (%)	10.99	-3.06	1.25	4.78	10.52	15.50	16.25	11.75
Median 1st day return (%)	4.17	-3.01	0.42	0.29	9.09	10.90	11.83	2.14
Mean price adjustment (%)	-8.08	-7.15	-10.50	-12.28	-1.54	-7.76	-5.53	-11.25
Median price adjustment (%)	-6.67	-6.23	-13.33	-13.33	-3.23	-4.28	-5.56	-8.33
Mean pre-IPO book asset ($ in mil.)	757	415	713	626	546	1,097	763	800
Median pre-IPO book asset ($ in mil.)	154	248	156	159	127	121	134	191
% of Hi-Tech IPOs	29.83	20.00	9.09	31.43	45.45	37.84	29.41	21.31

Table 2.2: IPO Allocations to Affiliated Mutual Funds

The table summarizes IPO allocations to affiliated mutual funds. Affiliated mutual funds are mandated by SEC Rule 10(f)-3 to disclose in N-SAR filings any allocation of IPOs underwritten by affiliated investment banks. IPOs were issued between 2008 and 2014 and exclude unit offerings, American Depository Receipts (ADRs) , Real Estate Investment Trusts (REITs), closed-end funds, limited partnerships (LPs), depository institutions, and Savings & Loans (S&Ls). Also excluded are IPOs of which affiliated investment banks did not act as lead- or co-manager. Panel A shows IPO allocations at the individual fund level. Allocation as % of IPO offering is the shares allocated divided by the total shares offered in the IPO. Allocation as % of fund TNA is the dollar amount allocated divided by the TNA of the fund. Fund TNA is the total net asset as of the end of the month or quarter nearest to the IPO issuance date. First-day return contribution is the dollar amount gain/loss of an IPO allocation in its first-day trading divided by the fund's TNA. Panel B shows summary statistics of IPO allocations aggregated to the investment bank level. It is common that more than one mutual fund advisors are affiliated with the same investment bank. Lead rank measures the prestige status of an investment bank, as defined in Carter and Manaster (1990). % of alloted shares is the percentage of IPO shares alloted to the investment bank in the syndicate. Allocation as % of AUM is the dollar amount of IPOs allocated to all mutual funds affiliated with the investment bank divided by the total AUMs by the affiliated mutual fund advisors. Panel C shows summary statistics of IPO allocations aggregated to the IPO level.

	2008-2014	2008	2009	2010	2011	2012	2013	2014
Panel A: Total allocations at fund level								
Number of allocations	3,302	87	415	388	493	423	782	714
Mean allocation as % of IPO offering	0.27	0.16	0.19	0.31	0.20	0.33	0.29	0.28
Mean allocation as % of fund TNA	0.22	0.62	0.25	0.16	0.19	0.51	0.16	0.11
Mean fund TNA ($ in mil)	888	904	661	707	780	730	1,164	1,000
Mean first-day return contribution (bps)	3.55	16.84	4.15	1.36	3.65	4.94	4.23	1.66
Panel B: Allocations at investment bank level								
Number of allocations	463	17	54	58	60	60	108	106
Mean number of funds allocated per IPO	6.39	4.88	7.28	5.97	7.68	5.98	6.4	5.91
Mean allocation as % of IPO offering	1.78	0.8	1.38	2.05	1.62	2.14	1.92	1.73
Number of allocations by lead manager	350	10	35	40	44	44	90	87
Mean lead rank	8.62	8.71	8.65	8.6	8.66	8.57	8.64	8.59
Mean % of alloted shares	19.4	14.23	19.49	19.97	18.98	19.81	18.75	20.46
Mean number of funds under management	54.52	41.47	76.15	74.33	64.05	44.4	46.27	43.5
Mean asset under management ($ in mil)	58,588	45,735	51,690	64,198	56,778	41,133	57,925	72,675
Mean allocation as % of AUM	0.03	0.05	0.02	0.02	0.03	0.06	0.03	0.01
Panel C: Allocations at IPO level								
Number of IPOs	270	7	27	35	31	36	62	72
Mean number of affiliated investment banks	3.17	3.86	3.41	3.31	3.23	2.92	3.26	2.96
Mean % of shares alloted to affiliated investment banks	58.76	69.77	64.65	68.42	59.95	57.27	56.23	53.48
Mean number of allocations	14.12	15.57	17.44	13.09	17.81	13.64	14.52	11.56
Mean % of shares allocated to affiliated advisers	2.93	1.83	2.71	3.17	3.09	3.32	3.26	2.48

Table 2.3: IPO Allocations to Affiliated Mutual Funds: Main-Advised vs. Sub-Advised

The table summarizes IPO allocations to affiliated mutual funds where affiliated fund advisers serve as main- or sub-advisers. It is common that an insurance company-sponsored mutual fund hires an affiliated fund adviser to manage a portion of its fund portfolio. Panel A shows IPO allocations to mutual funds of which an affiliated fund adviser serves as the main adviser. Panel B shows IPO allocations to mutual funds of which an affiliated fund adviser serves as the subadviser. Allocation as % of IPO offering is the shares allocated divided by the total shares offered in the IPO. Allocation as % of fund TNA is the dollar amount allocated divided by the TNA of the fund. Fund TNA is the total net asset as of the end of the month or quarter nearest to the IPO issuance date. First-day return contribution is the dollar amount gain/loss of an IPO allocation in its first-day trading divided by the fund's TNA.

	2008-2014	2008	2009	2010	2011	2012	2013	2014
Panel A: Main-advised funds								
Number of allocations	1,954	44	217	195	288	305	505	400
Mean allocation as % of IPO offering	0.34	0.21	0.21	0.38	0.27	0.40	0.36	0.40
Mean allocation as % of fund TNA	0.24	0.42	0.33	0.18	0.20	0.54	0.17	0.12
Mean fund TNA ($ in mil)	1,027	1,139	631	555	887	839	1,332	1,301
Mean 1st day return contribution (%)	0.05	0.11	0.04	0.01	0.11	0.07	0.05	0.02
Panel B: Sub-advised funds								
Number of allocations	1,236	32	109	141	189	141	301	323
Mean allocation as % of IPO offering	0.11	0.07	0.10	0.11	0.12	0.09	0.13	0.09
Mean allocation as % of fund TNA	0.18	0.23	0.26	0.17	0.19	0.41	0.13	0.09
Mean fund TNA ($ in mil)	600	376	288	510	570	511	859	591
Mean 1st day return contribution (%)	0.04	0.07	0.06	0.01	0.05	0.04	0.07	0.01

Table 2.4: Discrepancies between Actual Allocations and Reported Holdings as Proxy for Actual Allocations

The table summarizes discrepancies between actual allocations and reported holdings of IPOs as proxy for actual allocations to affiliated mutual funds. I follow Ritter and Zhang (2007) in terms of identifying investment bank-affiliated mutual funds and using their nearest quarter-end reported holdings of IPOs as proxy for actual allocations. In order to mitigate the discrepancies from using quarter-end reported holdings as proxy for actual allocations, RZ use a dummy variable method arguing that affiliated mutual funds are unlikely to liquidate their entire IPO allocations before the nearest quarter end. Following their method, I aggregate the fund-level allocations to the IPO level. Column “Allocated and reported” summarizes the IPOs that are both allocated to and reported positive holdings by affiliated mutual funds. Column “Not allocated but reported” summarizes the IPOs that are not allocated to but reported positive holdings by affiliated mutual funds. Column “Allocated but not reported” summarizes the IPOs that are allocated to but not reported positive holdings (zero holdings) by affiliated mutual funds. % allocation is the percentage of IPO offering allocated to all affiliated mutual funds. % holdings reported is the percentage of IPO shares reported in the nearest quarter end. % difference is the percentage difference between actual allocations and reported holdings. Adjustment is the price adjustment from the mid-point of the IPO filing range to the final offer price. 1st day return is the percentage change from the IPO offer price to the 1st day close price. Similar calculation applies to the 14-, 30-, 60-, and 90-day return.

	Allocated and reported	Not allocated but reported	Allocated but not reported
Number of IPOs	233	35	34
Mean % allocation	3.14	0.00	1.79
Mean % holdings reported	3.65	1.94	0.00
Mean % difference	0.51	1.94	-1.79
Mean adjustment (%)	2.92	-6.61	4.82
Mean 1st day return (%)	19.96	9.76	30.18
Mean 14-day return (%)	20.27	10.26	32.62
Mean 30-day return (%)	22.28	15.34	35.42
Mean 60-day return (%)	25.29	16.35	38.45
Mean 90-day return (%)	27.17	12.66	40.95
Mean offering ($ in mil.)	621	258	265
Mean pre-offer asset ($ in mil.)	4,352	1,722	1,075

Table 2.5: IPO Holdings of Unaffiliated Mutual Funds Reported in the Nearest Quarter End

The table summarizes IPO holdings of unaffiliated mutual funds reported in the nearest quarter end within 6 months of IPO issuance date. To qualify, an IPO has to be underwritten by one of the affiliated investment banks between 2008 and 2014. And the IPO cannot be an unit offering, American Depository Receipts (ADRs) , Real Estate Investment Trusts (REITs), closed-end funds, limited partnerships (LPs), depository institutions, or Savings & Loans (S&Ls). Panel A shows summary statistics of holdings by unaffiliated mutual funds of IPOs underwritten by affiliated investment banks. Panel B shows summary statistics of IPOs that are held by unaffiliated mutual funds and allocated to affiliated mutual funds. Panel C shows summary statistics of IPOs that are held by unaffiliated mutual funds but not allocated to affiliated mutual funds.

	2008-2014	2008	2009	2010	2011	2012	2013	2014
Panel A: IPOs allocated to unaffiliated mutual funds								
Number of IPOs	496	17	38	70	63	73	105	130
Mean number of funds allocated per IPO	66	46	46	58	79	77	76	59
Mean Allocation (%)	28.71	22.87	21.48	27.85	34.08	32.66	27.08	28.60
Mean allocation per fund (%)	0.62	1.19	0.46	0.59	0.53	0.59	0.60	0.68
Mean allocation as percentage of fund TNA (%)	0.55	0.52	0.66	0.41	0.28	0.22	0.37	1.05
Mean fund TNA (in mil.)	4,170	1,843	1,497	1,804	2,067	1,865	4,945	8,250
Mean 1st day return (%)	16.45	5.38	11.29	9.93	15.92	19.08	22.36	16.55
Mean adjustment (%)	-2.14	-3.51	-1.40	-7.49	3.42	-0.60	-0.34	-4.40
Mean pre-offer asset (in mil.)	2,466	1,429	1,092	3,039	1,724	1,215	3,414	2,939
% of tech IPOs	33.67	17.65	28.95	31.43	42.86	41.10	31.43	31.54
Panel B: IPOs allocated to both unaffiliated and affiliated mutual funds								
Number of IPOs	266	7	27	35	31	36	59	71
Mean number of funds allocated per IPO	83	85	54	70	97	104	95	72
Mean Allocation (%)	31.69	22.55	24.13	29.29	38.58	34.82	30.59	33.01
Mean allocation per fund (%)	0.50	0.58	0.42	0.56	0.45	0.43	0.48	0.55
Mean allocation as percentage of fund TNA (%)	0.52	0.86	0.30	0.50	0.27	0.24	0.36	0.99
Mean fund TNA (in mil.)	4,532	2,181	1,544	1,987	2,534	2,061	5,213	8,715
Mean 1st day return (%)	21.25	17.43	15.38	15.07	21.67	22.77	27.38	20.61
Mean adjustment (%)	3.10	1.70	2.30	-2.70	8.69	6.76	3.92	1.41
Mean pre-offer asset (in mil.)	3,912	3,117	1,252	5,453	3,019	1,333	5,447	4,539
% of tech IPOs	36.09	14.29	37.04	31.43	38.71	44.44	30.51	39.44
Panel C: IPOs allocated to unaffiliated but not affiliated mutual funds								
Number of IPOs	230	10	11	35	32	37	46	59
Mean number of funds allocated per IPO	47	18	25	46	62	52	50	43
Mean Allocation (%)	25.32	23.09	14.98	26.41	29.84	30.55	22.82	23.41
Mean allocation per fund (%)	0.76	1.62	0.54	0.62	0.61	0.75	0.74	0.84
Mean allocation as percentage of fund TNA (%)	0.57	0.28	1.53	0.32	0.29	0.20	0.38	1.14
Mean fund TNA (in mil.)	3,750	1,606	1,383	1,620	1,615	1,675	4,601	7,680
Mean 1st day return (%)	10.99	-3.06	1.25	4.78	10.52	15.50	16.25	11.75
Mean adjustment (%)	-8.08	-7.15	-10.50	-12.28	-1.54	-7.76	-5.53	-11.25
Mean pre-offer asset (in mil.)	778	415	675	626	547	1,100	788	872
% of tech IPOs	30.87	20.00	9.09	31.43	46.88	37.84	32.61	22.03

Table 2.6: Determinants of IPO Purchases and Percentage Allocations

The table shows the regression results of determinants of IPO purchases and percentage allocations. In regression [1], the dependent variable, $PurchaseDummy$, is 1 if the IPO is allocated and 0 otherwise. In regression [2], the dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. In regression [3], the dependent variable, $PerfBoost$, is the contribution of first-day return (%) of the IPO allocations to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. 1stDayRet is the percentage change from the IPO final offer price to its first-day closing price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). LeadManagerDummy is 1 if the investment bank serves as a lead manager in the syndicate and 0 if co-manager. TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. Ln(AUM) is the natural log of the total asset under management by the fund adviser affiliated with the investment bank. PctAllotment is the percentage of IPO shares alloted to the investment bank in the syndicate. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. P-value is shown in parenthesis.

	[1]		[2]		[3]	
	DepVar: $PurchaseDummy$		DepVar: $PctAllocation$		DepVar: $PerfBoost$	
Adjustment	0.043***		-0.036***		0.388	
	(0.000)		(0.000)		(0.514)	
1stDayRet		0.019***		-0.012***		1.398***
		(0.000)		(0.003)		(0.000)
Ln(Asset)	0.090***	0.118***	-0.144**	-0.128*	11.300**	18.999***
	(0.002)	(0.000)	(0.024)	(0.054)	(0.020)	(0.000)
LeadRank	-0.028	0.022	-0.092	0.055	44.982	45.828
	(0.963)	(0.970)	(0.939)	(0.964)	(0.620)	(0.603)
LeadManagerDummy	-0.093	-0.07	-0.145	-0.139	4.069	7.596
	(0.519)	(0.619)	(0.633)	(0.651)	(0.861)	(0.737)
TechDummy	0.337***	0.388***	0.197	0.198	38.426**	39.220**
	(0.001)	(0.000)	(0.344)	(0.349)	(0.016)	(0.011)
Ln(AUM)	0.138	0.012	0.349	0.457	3.495	-2.664
	(0.353)	(0.934)	(0.319)	(0.199)	(0.895)	(0.918)
PctAllotment	-0.010**	-0.011**	0.012	0.015	1.179	1.265
	(0.040)	(0.021)	(0.269)	(0.163)	(0.143)	(0.105)
OverAllotmentDummy	0.191*	0.096	0.429*	0.520*	19.16	-14.952
	(0.084)	(0.388)	(0.093)	(0.058)	(0.329)	(0.458)
Observations	1,279	1,279	440	440	427	427
R2	27.7%	22.9%	15.6%	12.9%	9%	14.2%
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Underwriter-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7: Determinants of IPO Purchases and Percentage Allocations: Sub-Period Regressions

The table shows the regression results of determinants of IPO purchases and percentage allocations in three sub-periods, 2008-2010, 2011-2012, and 2013-2014. In Panel A, the dependent variable, $PurchaseDummy$, is 1 if the IPO is allocated and 0 otherwise. In Panel B, the dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. In Panel C, the dependent variable, $PerfBoost$, is the contribution of first-day return (%) of the IPO allocations to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. 1stDayRet is the percentage change from the IPO final offer price to its first-day closing price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). LeadManagerDummy is 1 if the investment bank serves as a lead manager in the syndicate and 0 if co-manager. TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. Ln(AUM) is the natural log of the total asset under management by the fund adviser affiliated with the investment bank. PctAllotment is the percentage of IPO shares alloted to the investment bank in the syndicate. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. P-value is shown in parenthesis.

	2008-2010	2011-2012	2013-2014	2008-2010	2011-2012	2013-2014
Panel A: $PurchaseDummy$						
Adjustment	0.034***	0.050***	0.051***			
	(0.000)	(0.000)	(0.000)			
1stDayRet				0.028***	0.024***	0.016***
				(0.000)	(0.000)	(0.000)
Observations	345	324	610	345	324	610
R2	21.2%	33.7%	32.4%	19.6%	27.3%	26.2%
Underwriter-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Ln(Asset), LeadRank, LeadManagerFlag, TechDummy, Ln(AUM), PctAllotment, OverAllotmentDummy						
Panel B: $PctAllocation$						
Adjustment	-0.056***	-0.028*	-0.030***			
	(0.001)	(0.080)	(0.006)			
1stDayRet				-0.042***	0	-0.008*
				(0.002)	(0.969)	(0.070)
Observations	120	112	208	120	112	208
R2	17.1%	11.5%	17.7%	16.3%	8.6%	15.9%
Underwriter-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Ln(Asset), LeadRank, LeadManagerFlag, TechDummy, Ln(AUM), PctAllotment, OverAllotmentDummy						
Panel C: $PerfBoost$						
Adjustment	1.531***	-1.92	1.040*			
	(0.008)	(0.334)	(0.087)			
1stDayRet				1.312***	3.846***	0.731***
				(0.002)	(0.000)	(0.002)
Observations	115	108	204	115	108	204
R2	5.3%	14.3%	6.6%	7.7%	26.6%	9.7%
Underwriter-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Ln(Asset), LeadRank, LeadManagerFlag, TechDummy, Ln(AUM), PctAllotment, OverAllotmentDummy						

Table 2.8: Determinants of IPO Purchases and Percentage Allocations: Investment Bank-Level Regressions

The table shows the regression results of determinants of IPO purchases and percentage allocations in subsamples divided by investment banks. Investment banks other than J.P. Morgan (JPM), Goldman Sachs (GS), Morgan Stanley (MS), Wells Fargo (WF), and Deutsche Bank (DB) are merged into Others. In Panel A, the dependent variable, $PurchaseDummy$, is 1 if the IPO is allocated and 0 otherwise. In Panel B, the dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. In Panel C, the dependent variable, $PerfBoost$, is the contribution of first-day return (%) of the IPO allocations to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. 1stDayRet is the percentage change from the IPO final offer price to its first-day closing price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). LeadManagerDummy is 1 if the investment bank serves as a lead manager in the syndicate and 0 if co-manager. TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. Ln(AUM) is the natural log of the total asset under management by the fund adviser affiliated with the investment bank. PctAllotment is the percentage of IPO shares alloted to the investment bank in the syndicate. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. P-value is shown in parenthesis.

	JPM	GS	MS	WF	DB	Others	JPM	GS	MS	WF	DB	Others
Panel A: $PurchaseDummy$												
Adjustment	0.038***	0.054***	0.047***	0.052***	0.060***	0.043***						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
1stDayRet							0.016***	0.012***	0.027***	0.039***	0.022***	0.020***
							(0.001)	(0.003)	(0.000)	(0.003)	(0.000)	(0.000)
Observations	237	210	222	134	173	302	237	210	222	134	173	302
R2	19.5%	18.4%	20%	32.9%	32.1%	23.5%	13%	6.8%	22.1%	25.3%	25.4%	20.8%
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Ln(Asset), LeadRank, LeadManagerFlag, TechDummy, Ln(AUM), PctAllotment, OverAllotmentDummy												
Panel B: $PctAllocation$												
Adjustment	-0.038***	-0.061**	-0.094**	0.01	-0.089**	-0.096***						
	(0.002)	(0.012)	(0.043)	(0.248)	(0.024)	(0.000)						
1stDayRet							-0.019**	-0.022**	-0.007	0.013**	-0.025	-0.007
							(0.010)	(0.049)	(0.740)	(0.011)	(0.165)	(0.424)
Observations	154	62	41	87	37	59	154	62	41	87	37	59
R2	4.6%	24%	10.6%	22.4%	35.7%	27.3%	2.8%	19.9%	-4.5%	27.6%	25.9%	1.8%
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Ln(Asset), LeadRank, LeadManagerFlag, TechDummy, Ln(AUM), PctAllotment, OverAllotmentDummy												
Panel C: $PerfBoost$												
Adjustment	0.63	1.147**	-10.223	0.374*	0	1.195						
	(0.133)	(0.029)	(0.116)	(0.081)	(1.000)	(0.350)						
1stDayRet							0.837***	0.830***	5.053*	0.493***	0.105	0.245
							(0.001)	(0.000)	(0.087)	(0.000)	(0.449)	(0.550)
Observations	154	62	40	76	37	58	154	62	40	76	37	58
R2	10.8%	16.3%	0.4%	10.1%	4.8%	-4.1%	16.7%	29.3%	2.3%	31.9%	7.2%	-5.3%
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Ln(Asset), LeadRank, LeadManagerFlag, TechDummy, Ln(AUM), PctAllotment, OverAllotmentDummy												

Table 2.9: Within-Fund Families IPO Purchases and Percentage Allocations

The table summarizes IPO purchase decision and percentage allocation at the individual fund level within the fund family. In regression [1], the dependent variable, $PurchaseDummy$, is 1 if the IPO is allocated and 0 otherwise. In regression [2], the dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. In regression [3], the dependent variable, $PerfBoost$, is the contribution of first-day return (%) of the IPO allocations to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. 1stDayRet is the percentage change from the IPO final offer price to its first-day closing price. ExpenseRatio is the annual gross expense charged by the affiliated mutual fund. PastAlpha measures the risk-adjusted past performance of the individual fund, which is the alpha from regressing past 12-month returns on the Fama-French-Carhart four factors. Ln(TNA) is the natural log of the fund's TNA prior to the IPO allocation. Ln(Age) is the natural log of the fund's age in months prior to the IPO allocation. P-value is shown in parenthesis.

	[1]		[2]		[3]	
	Dep Var: $PurchaseDummy$		DepVar: $PctAllocation$		DepVar: $PerfBoost$	
Adjustment	-0.018		0.057**		1.939	
	(0.107)		(0.014)		(0.491)	
1stDayRet		-0.015***		0.011		-0.99
		(0.004)		(0.281)		(0.413)
ExpenseRatio	21.056***	15.046**	62.149***	68.333***	-581.519	-476.723
	(0.000)	(0.027)	(0.000)	(0.000)	(0.688)	(0.777)
PastAlpha	2.157	-4.716	38.389***	24.558**	1816.237	3126.195**
	(0.536)	(0.260)	(0.000)	(0.022)	(0.118)	(0.017)
Ln(TNA)	0.004	-0.001	0.346***	0.304***	-13.007***	-18.301***
	(0.724)	(0.924)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Age)	0.412***	0.375***	-0.028	-0.028	-11.636*	-13.240*
	(0.000)	(0.000)	(0.620)	(0.669)	(0.094)	(0.092)
ExpenseRatio * Adjustment	1.802***		-2.311***		-6.434	
	(0.000)		(0.002)		(0.943)	
PastAlpha * Adjustment	0.211		-1.642**		31.202	
	(0.396)		(0.013)		(0.714)	
Ln(TNA) * Adjustment	0		-0.011***		-0.163	
	(0.596)		(0.000)		(0.389)	
Ln(Age) * Adjustment	0.001		0.005		-0.144	
	(0.641)		(0.252)		(0.770)	
ExpenseRatio * 1stDayRet		0.693***		-0.921***		-1.897
		(0.000)		(0.007)		(0.963)
PastAlpha * 1stDayRet		0.367***		0.137		-36.336
		(0.002)		(0.602)		(0.250)
Ln(TNA) * 1stDayRet		0		-0.001**		0.137*
		(0.393)		(0.027)		(0.083)
Ln(Age) * 1stDayRet		0.002**		0.001		0.008
		(0.048)		(0.647)		(0.968)
Observations	18,740	18,740	1,491	1,491	1,443	1,443
R2	6.3%	6.2%	26.4%	21.9%	5.3%	5.6%
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Fund-family fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.10: Within-Fund Families IPO Percentage Allocations: Fund Family-Level Regressions

The table summarizes IPO percentage allocation at the individual fund level within the fund family of each affiliated investment bank. For example, mutual funds advised by J.P.Morgan Asset Management are categorized under the label JPM. Similar categorization applies to funds advised by WCM (Wells Capital Management), GSAM (Goldman Sachs Asset Management), AC (American Century). The rest are categorized under the label Other. The dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. 1stDayRet is the percentage change from the IPO final offer price to its first-day closing price. ExpenseRatio is the annual gross expense charged by the affiliated mutual fund. PastAlpha measures the risk-adjusted past performance of the individual fund, which is the alpha from regressing past 12-month returns on the Fama-French-Carhart four factors. Ln(TNA) is the natural log of the fund's TNA prior to the IPO allocation. Ln(Age) is the natural log of the fund's age in months prior to the IPO allocation. P-value is shown in parenthesis.

	JPM		WCM		GSAM		AC		Others	
Adjustment	0.070*		0.023		0.189**		0.047		0.031	
	(0.057)		(0.619)		(0.032)		(0.405)		(0.761)	
1stDayRet		0.02		0.016		0.084**		-0.019		0.009
		(0.262)		(0.435)		(0.022)		(0.749)		(0.812)
ExpenseRatio	115.277***	111.501***	4.547	26.589	114.478*	165.446**	55.122*	74.234*	-44.449	-24.396
	(0.000)	(0.000)	(0.883)	(0.467)	(0.071)	(0.031)	(0.060)	(0.060)	(0.366)	(0.668)
PastAlpha	70.077***	61.836***	15.24	20.432	56.508	81.926	38.074*	67.607**	21.223	-42.964
	(0.000)	(0.000)	(0.244)	(0.172)	(0.210)	(0.107)	(0.066)	(0.017)	(0.568)	(0.292)
Ln(TNA)	0.321***	0.331***	0.198***	0.192***	0.315***	0.275**	0.383***	0.301***	0.379***	0.268**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.013)	(0.000)	(0.002)	(0.000)	(0.010)
Ln(Age)	0.165**	0.170**	-0.155	-0.171	0.124	0.318	-0.445***	-0.426**	0.202	0.326
	(0.015)	(0.049)	(0.160)	(0.114)	(0.694)	(0.399)	(0.005)	(0.020)	(0.348)	(0.177)
ExpenseRatio * Adjustment	-3.420***		-0.125		-3.836		-3.802		3.565	
	(0.000)		(0.953)		(0.334)		(0.186)		(0.301)	
PastAlpha * Adjustment	-3.054***		-0.224		-3.919		-3.973		1.468	
	(0.002)		(0.804)		(0.100)		(0.106)		(0.566)	
Ln(TNA) * Adjustment	-0.012***		0.002		-0.004		-0.028***		-0.012	
	(0.000)		(0.561)		(0.542)		(0.002)		(0.103)	
Ln(Age) * Adjustment	0.005		-0.008		-0.033		0.033**		-0.002	
	(0.421)		(0.283)		(0.100)		(0.032)		(0.874)	
ExpenseRatio * 1stDayRet		-0.625		-0.742		-2.788*		-2.014		0.578
		(0.151)		(0.414)		(0.098)		(0.307)		(0.671)
PastAlpha * 1stDayRet		-0.355		-0.2		-1.448		-3.095**		1.891**
		(0.475)		(0.555)		(0.144)		(0.039)		(0.015)
Ln(TNA) * 1stDayRet		-0.003***		0.001		0		-0.006		0.002
		(0.003)		(0.528)		(0.922)		(0.123)		(0.531)
Ln(Age) * 1stDayRet		0		-0.003		-0.013		0.014		-0.005
		(0.960)		(0.320)		(0.130)		(0.110)		(0.368)
Observations	728	728	238	238	139	139	133	133	253	253
R2	30.6%	23.5%	21.2%	19.4%	45.9%	39%	21.7%	14.5%	18.9%	16.4%
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.11: Determinants of IPO purchases and percentage allocations: actual allocations vs. reported holdings

The table compares the results of determinants of IPO purchases and percentage allocations using actual allocations vs. reported holdings of IPOs aftermarket. Actual allocations are disclosed in semi-annually filed N-SAR forms. Reported holdings of IPOs are disclosed in the nearest quarter-end N-Q or N-CSR filings. The dependent variable, $PurchaseDummy$, is 1 if the IPO is allocated and 0 otherwise. The dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. PctAllotment is the percentage of IPO shares alloted to the investment bank in the syndicate. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. P-value is shown in parenthesis.

	Actual Allocations		Reported Holdings	
	Dep Var: $PurchaseDummy$	Dep Var: $PctAllocation$	Dep Var: $PurchaseDummy$	Dep Var: $PctAllocation$
Adjustment	0.039***	-0.028*	0.028***	-0.003
	(0.000)	(-1.89)	(0.000)	(-0.13)
Ln(Asset)	0.268***	0.052	0.190***	0.276
	(0.000)	(0.44)	(0.000)	(1.43)
LeadRank	0.650***	0.222	0.796***	2.006
	(0.003)	(0.23)	(0.000)	(1.56)
TechDummy	0.219	0.273	0.335**	1.295**
	(0.148)	(0.62)	(0.014)	(2.14)
PctAllotment	0.010***	0.040***	-0.014*	0.017
	(0.007)	(3.57)	(0.074)	(0.52)
OverAllotmentDummy	0.261	0.721	-0.1	0.745
	(0.108)	(1.40)	(0.509)	(1.07)
Sample size	499	263	502	264
Adjusted R2	26.2%	8.9%	17.3%	6.4%
Year-fixed effect	Yes	Yes	Yes	Yes

Table 2.12: Within-Fund Families IPO Allocations: Reported Holdings

The table summarizes IPO percentage allocation at the individual fund level within the fund family, using reported holdings of IPOs in the nearest quarter end. In regression [1], the dependent variable, $PurchaseDummy$, is 1 if the IPO is allocated and 0 otherwise. In regression [2], the dependent variable, $PctAllocation$, is the percentage of IPO offering allocated to mutual funds affiliated with the investment bank. In regression [3], the dependent variable, $PerfBoost$, is the contribution of first-day return (%) of the IPO allocations to mutual funds affiliated with the investment bank. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. 1stDayRet is the percentage change from the IPO final offer price to its first-day closing price. ExpenseRatio is the annual gross expense charged by the affiliated mutual fund. PastAlpha measures the risk-adjusted past performance of the individual fund, which is the alpha from regressing past 12-month returns on the Fama-French-Carhart four factors. Ln(TNA) is the natural log of the fund's TNA prior to the IPO allocation. Ln(Age) is the natural log of the fund's age in months prior to the IPO allocation. P-value is shown in parenthesis.

	[1]		[2]		[3]	
	Dep Var: $PurchaseDummy$		DepVar: $PctAllocation$		DepVar: $PerfBoost$	
Adjustment	-0.024**		0.096**		0.622	
	(0.030)		(0.011)		(0.207)	
1stDayRet		-0.012**		0.02		1.964***
		(0.041)		(0.320)		(0.000)
ExpenseRatio	-0.103	-2.85	70.342***	97.664***	349.774	231.727
	(0.985)	(0.657)	(0.000)	(0.000)	(0.111)	(0.344)
PastAlpha	6.273*	1.873	65.437***	44.239**	291.866	-62.841
	(0.072)	(0.652)	(0.000)	(0.010)	(0.123)	(0.764)
Ln(TNA)	-0.058***	-0.055***	0.524***	0.499***	-0.565	1.326***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.186)	(0.006)
Ln(Age)	0.483***	0.457***	-0.162*	-0.205**	-2.447**	0.787
	(0.000)	(0.000)	(0.055)	(0.040)	(0.026)	(0.518)
ExpenseRatio * Adjustment	1.165***		-4.142***		16.141	
	(0.002)		(0.000)		(0.265)	
PastAlpha * Adjustment	0.26		2.589**		45.106***	
	(0.294)		(0.021)		(0.002)	
Ln(TNA) * Adjustment	0		-0.012***		-0.031	
	(0.946)		(0.000)		(0.323)	
Ln(Age) * Adjustment	0.003		0.002		-0.084	
	(0.130)		(0.770)		(0.313)	
ExpenseRatio * 1stDayRet		0.331*		-2.248***		5.288
		(0.097)		(0.000)		(0.472)
PastAlpha * 1stDayRet		0.317**		1.681***		23.113***
		(0.023)		(0.001)		(0.000)
Ln(TNA) * 1stDayRet		0		-0.002		-0.094***
		(0.744)		(0.192)		(0.000)
Ln(Age) * 1stDayRet		0.002*		0.002		-0.234***
		(0.075)		(0.622)		(0.000)
Sample size	17,270	17,270	1,414	1,414	1,414	1,414
R2	5.8%	5.6%	30.1%	29.2%	25.2%	33.7%

Table 2.13: Determinants of IPO Percentage Allocations Proxied by Nearest Quarter-End Reported Holdings: Unaffiliated Mutual Funds

The table shows the determinants of IPO percentage allocations to unaffiliated mutual funds as a group. The IPO allocations are proxied by the nearest quarter-end reported holdings within 6 months' of IPO issuance. The dependent variable, $PctAllocation$, is the % of IPO shares held by unaffiliated mutual funds at the nearest quarter end. Panel A shows the OLS regression results for all IPOs held by unaffiliated mutual funds. Panel B shows the OLS regression results for IPOs both allocated to affiliated mutual funds and held by unaffiliated mutual funds. Panel C shows the OLS regression results for IPOs not allocated to affiliated mutual funds but held by unaffiliated mutual funds. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. T-stat is reported in parenthesis.

	2008-2014	2008-2010	2011-2012	2013-2014
Panel A: IPOs held by unaffiliated mutual funds				
Adjustment	0.174***	-0.029	0.239***	0.163**
	(3.39)	(-0.24)	(3.35)	(2.10)
Ln(Asset)	0.051	-0.05	0.919	-0.43
	(0.12)	(-0.05)	(0.82)	(-0.73)
LeadRank	1.385	-6.657	-0.159	6.321***
	(0.78)	(-1.32)	(-0.05)	(3.10)
TechDummy	4.001**	8.469**	4.867	1.851
	(2.22)	(2.41)	(1.28)	(0.75)
OverAllotmentDummy	8.118***	9.553***	9.635***	7.985***
	(5.37)	(2.91)	(3.48)	(3.72)
Sample size	482	122	135	225
Adjusted R2	10.9%	7.4%	10%	10%
Year-fixed effect	Yes			
Panel B: IPOs both allocated to affiliated and held by unaffiliated funds				
Adjustment	0.169**	0.086	0.359***	0.021
	(2.01)	(0.54)	(2.78)	(0.16)
Ln(Asset)	-1.061	-0.912	0.387	-2.014**
	(-1.57)	(-0.76)	(0.18)	(-2.03)
LeadRank	1.105	-17.304**	4.609	14.526**
	(0.24)	(-2.58)	(0.53)	(2.03)
TechDummy	2.998	2.556	4.687	0.12
	(1.06)	(0.59)	(0.59)	(0.03)
OverAllotmentDummy	6.364***	2.242	8.319*	10.720***
	(2.64)	(0.47)	(1.89)	(3.08)
Sample size	266	67	66	133
Adjusted R2	11.2%	11.9%	13.4%	9.9%
Year-fixed effect	Yes			
Panel C: IPOs not allocated to affiliated by held by unaffiliated funds				
Adjustment	0.014	-0.2	0.036	0.047
	(0.20)	(-0.87)	(0.34)	(0.50)
Ln(Asset)	0.839	0.495	1.286	0.434
	(1.17)	(0.35)	(0.82)	(0.43)
LeadRank	0.566	-5.441	-0.222	3.654*
	(0.30)	(-0.90)	(-0.06)	(1.76)
TechDummy	4.652*	10.492**	2.869	4.033
	(1.96)	(2.10)	(0.75)	(1.13)
OverAllotmentDummy	10.259***	12.135***	11.022***	7.819**
	(4.86)	(2.82)	(2.70)	(2.53)
Sample size	228	55	70	103
Adjusted R2	10.9%	11.4%	3.3%	5.6%
Year-fixed effect	Yes			

Table 2.14: IPO Percentage Allocation and First-Day Return: Affiliated Mutual Funds

The table shows the relation between IPO percentage allocations to affiliated mutual funds as group and the IPO's first-day return. The dependent variable, $FirstDayReturn$, is the percentage change of an IPO's offer price to its closing price of the first trading day. Allocation is the % of IPO allocated to affiliated mutual funds aggregated to the IPO level. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. PctAllotment is the percentage of IPO shares alloted to the investment bank in the syndicate. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. T-stat is reported in parenthesis.

	2008-2014	2008-2010	2011-2012	2013-2014
Allocation	0.189	-0.717*	1.178	-0.023
	(0.42)	(-1.96)	(1.20)	(-0.03)
Adjustment	0.778***	0.597***	0.529**	0.979***
	(6.85)	(4.40)	(2.24)	(5.01)
Ln(Asset)	-3.842***	-4.057***	-2.970*	-3.675***
	(-5.29)	(-3.38)	(-1.99)	(-3.11)
LeadRank	-2.573	-16.020*	9.627	-0.212
	(-0.29)	(-1.84)	(1.40)	(-0.01)
TechDummy	-4.315	-10.026**	-0.931	-3.053
	(-1.34)	(-2.54)	(-0.12)	(-0.59)
PctAllotment	0.148*	0.142	0.173	0.173
	(1.91)	(1.56)	(1.30)	(1.21)
OverAllotmentDummy	19.353***	18.668***	17.755***	21.350***
	(6.75)	(4.45)	(3.30)	(4.26)
Sample size	263	66	64	133
Adjusted R2	37.1%	52.7%	34.8%	35%
Year-fixed effect	Yes			

Table 2.15: IPO Percentage Allocation and First-Day Return: Unaffiliated Mutual Funds

The table shows the relation between IPO percentage allocations to unaffiliated mutual funds as a group and the IPO's first-day return. The IPO allocations are proxied by the nearest quarter-end reported holdings within 6 months' of IPO issuance. The dependent variable, $FirstDayReturn$, is the percentage change from the IPO's final offer price to its first-day closing price. Panel A shows the OLS regression results for all IPOs held by unaffiliated mutual funds. Panel B shows the OLS regression results for IPOs both allocated to affiliated mutual funds and held by unaffiliated mutual funds. Panel C shows the OLS regression results for IPOs not allocated to affiliated mutual funds but held by unaffiliated mutual funds. Allocation is the % of IPO shares held by unaffiliated mutual funds aggregated to the IPO level. Adjustment is the percentage change from the mid-point of the IPO filing range to its final offer price. Ln(Asset) is the natural log of the IPO issuer's pre-IPO book value. LeadRank measures the prestige status of an investment bank as defined in Carter and Manaster (1990). TechDummy is 1 if the IPO issuer is a tech company and 0 otherwise. OverAllotmentDummy is 1 if the overallotment option is exercised by the syndicate and 0 otherwise. T-stat is reported in parenthesis.

	2008-2014	2008-2010	2011-2012	2013-2014
Panel A: IPOs held by unaffiliated mutual funds				
Allocation	0.207***	0.169**	0.144	0.252**
	(3.48)	(2.41)	(1.39)	(2.44)
Adjustment	0.648***	0.551***	0.584***	0.733***
	(10.36)	(5.52)	(5.49)	(7.01)
Ln(Asset)	-2.884***	-1.672**	-1.495	-3.774***
	(-5.79)	(-2.00)	(-1.26)	(-5.48)
LeadRank	4.236**	-1.789	7.165**	4.781
	(2.10)	(-0.56)	(2.40)	(1.49)
TechDummy	0.822	-2.393	2.938	2.163
	(0.38)	(-0.85)	(0.70)	(0.60)
OverAllotmentDummy	15.680***	15.711***	18.169***	14.611***
	(9.25)	(7.01)	(5.28)	(4.75)
Sample size	482	122	135	225
Adjusted R2	40.2%	46.4%	37.2%	38.5%
Year-fixed effect	Yes			
Panel B: IPOs both allocated to affiliated and held by unaffiliated funds				
Allocation	0.168**	0.023	0.084	0.268**
	(2.15)	(0.20)	(0.61)	(2.07)
Adjustment	0.767***	0.674***	0.525**	1.003***
	(7.08)	(4.96)	(2.52)	(5.38)
Ln(Asset)	-3.922***	-4.034***	-3.660*	-3.238**
	(-4.54)	(-3.53)	(-1.96)	(-2.35)
LeadRank	2.502	-9.749	18.517	-1.601
	(0.38)	(-1.20)	(1.36)	(-0.14)
TechDummy	-4.022	-9.371**	0.147	-1.59
	(-1.28)	(-2.30)	(0.02)	(-0.30)
OverAllotmentDummy	17.859***	16.283***	17.530**	18.125***
	(4.75)	(3.39)	(2.65)	(2.71)
Sample size	266	67	66	133
Adjusted R2	37.9%	51.3%	32.8%	36.9%
Year-fixed effect	Yes			
Panel C: IPOs not allocated to affiliated but held by unaffiliated funds				
Allocation	0.163**	0.209***	0.184	0.067
	(2.17)	(3.04)	(1.24)	(0.52)
Adjustment	0.536***	0.127	0.584***	0.580***
	(6.44)	(1.15)	(3.77)	(4.42)
Ln(Asset)	-1.753**	-0.194	0.194	-3.572***
	(-2.29)	(-0.23)	(0.12)	(-2.94)
LeadRank	3.683	-3.63	5.357	7.223**
	(1.63)	(-1.42)	(1.11)	(2.04)
TechDummy	5.933**	2.016	3.633	9.392**
	(2.30)	(0.76)	(0.77)	(2.12)
OverAllotmentDummy	14.418***	9.923***	18.661***	12.177**
	(5.19)	(4.15)	(3.30)	(2.61)
Sample size	228	55	70	103
Adjusted R2	38.1%	40.7%	34.6%	37.3%
Year-fixed effect	Yes			

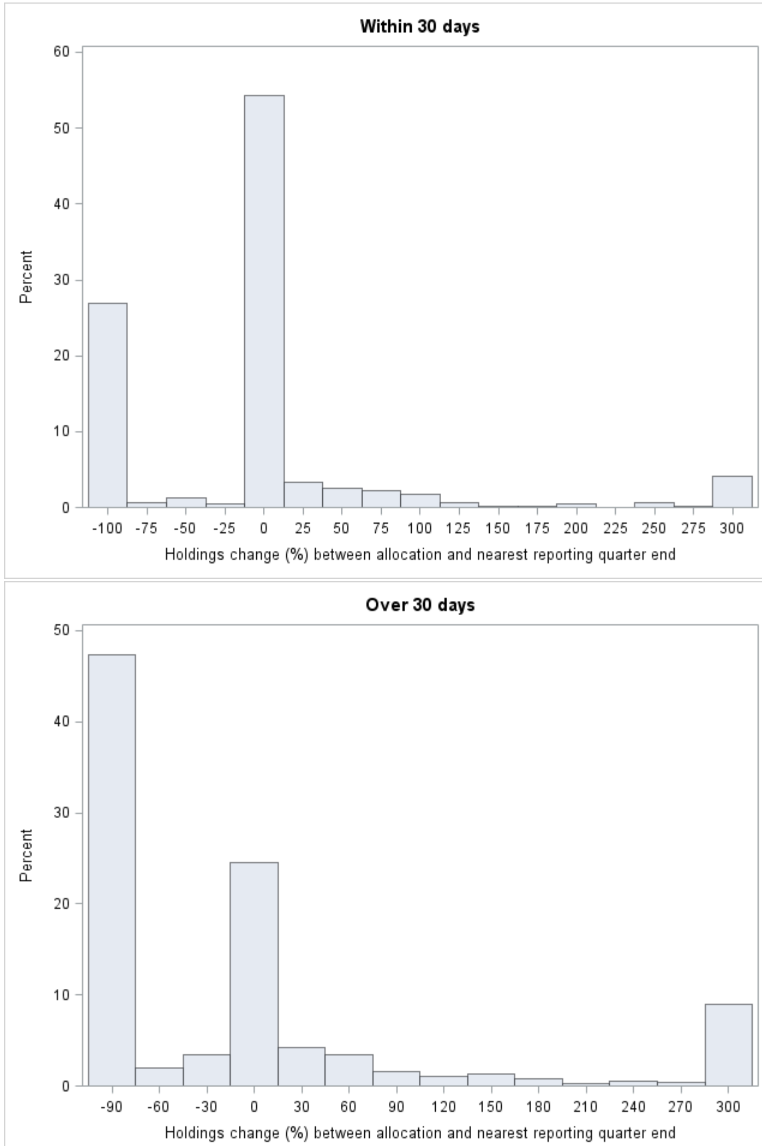

Figure 2. 1: Holdings Change between Allocation and Nearest Reporting Quarter End

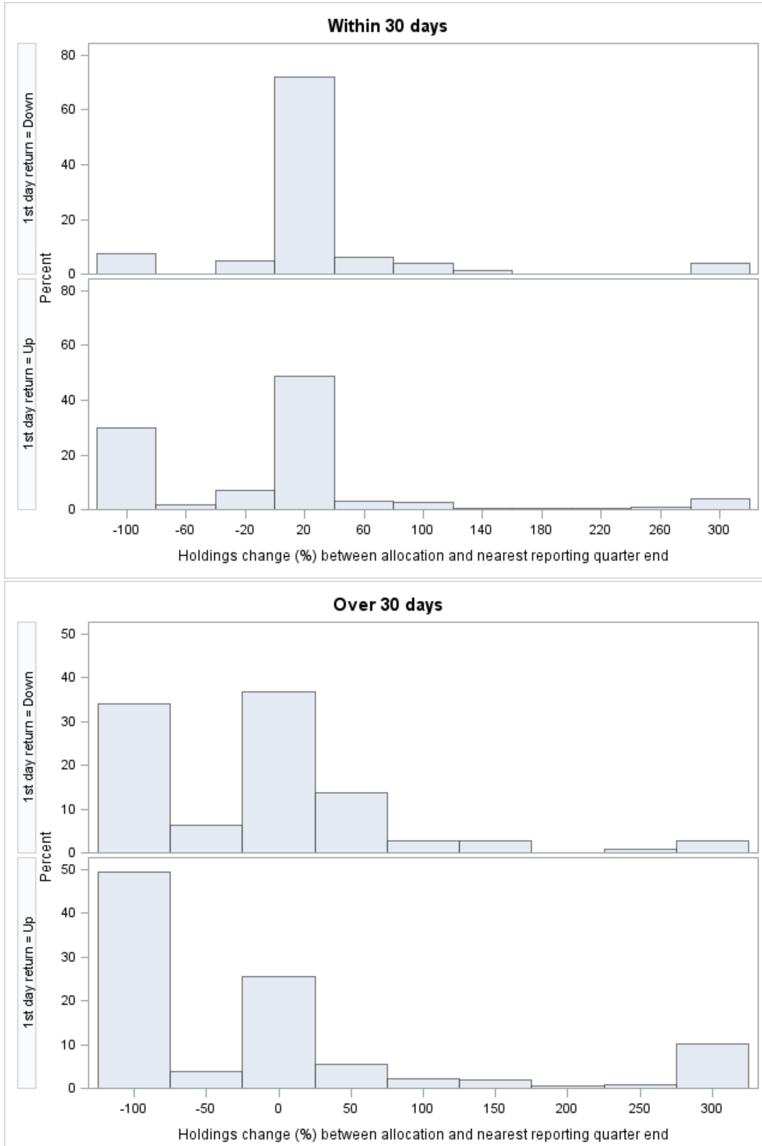

Figure 2. 2: Holdings Change between Allocation and Nearest Reporting Quarter End: 1st Day Return Up vs. 1st Day Return Down

Chapter 3
Mutual Fund Turnover and Performance Persistence

3.1 Introduction

The portfolio turnover rate measures how frequently a fund trades. It is a basic statistic that the Investment Company Act of 1940 requires mutual funds to disclose periodically to the public, presumably because information about portfolio turnover matters to investors when they decide on which funds to invest in. Conceptually, portfolio turnover may be related to investment performance in multiple ways. Funds may have high portfolio turnover because they face attractive investment opportunities in the near term. In this case turnover should positively predict performance. Meanwhile, it has also been observed that certain well-known investment managers, such as Bill Miller and Mario Gabelli, often hold their positions for a long period of time; low turnover is inherent to their successful investment strategies. In this case, patience (and low turnover) is virtue. Finally, high portfolio turnover may be associated with high trading cost, creating a hazardous impact on performance.

The relation between portfolio turnover and investment performance has been the subject of a long stream of empirical research. However the empirical evidence so far is clearly mixed. Earlier studies including Elton, Gruber, Hlavka (1993) and Carhart (1997) report that higher-turnover funds have worse performance. Subsequent studies such as Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Edelen, Evans, and Kadlec (2007), find no significant relation.[1] By contrast, Dahlquist, Engstrom and Soderlind (2000) and Chen, Jagadeesh and Wermers (2001) report that higher-turnover funds have better performance.

[1] Ippolito (1989), perhaps the earliest study on this topic, also reports that turnover has no significant impact on performance.

Two recent studies on this issue continue to report results that are quite different from each other. Pastor, Stambaugh, and Taylor (2017) find that turnover positively predicts performance, although they emphasize that the relation they find is a time-series effect for a given fund. Meanwhile, Cremers and Pareek (2016) find that among funds with a high degree of activeness, turnover is negatively related to performance across funds. It appears that despite a long history of research efforts on this topic, there is no clear consensus yet.

Our study contributes to the literature by reporting strong heterogeneity in the effects of turnover on fund performance, which, if ignored, may confound analysis and lead to mixed inferences. We study a large sample of actively managed US equity mutual funds during the period of 1980-2016. We find that the average performance of high-turnover funds is insignificantly different from that of low-turnover funds; however, relative to low-turnover funds, high-turnover funds exhibit much more dispersed performance, with some high-turnover funds experiencing large positive returns while others exhibiting large negative returns. Such performance dispersion suggests a possibility that high turnover may benefit the performance of some funds while negatively impact other funds. To make the implication of this finding more clear, consider the example illustrated in Figure 3.1. There are two high-turnover funds, A and B, and two low-turnover funds, C and D. Fund B and D do not have profitable investment opportunities available. Nonetheless, Fund B trades much more frequently than Fund D, thus incurring much higher trading costs. Between these two funds, there is a negative relation between turnover and performance, mainly driven by trading costs. On the other hand, Fund A and C trade aggressively in response to investment opportunities available. However, Fund A respond more aggressively to investment opportunities than Fund C while keeping the impact of trading costs in check. Thus, between these two funds, there is a positive relation between turnover and performance. As a consequence, the two high-turnover funds B and D have larger performance dispersion than the two low-turnover funds A and C. Meanwhile, the average performance of Fund A and C are similar to the average performance of Fund B and D. That is, if we only look at the average performance of the two funds, we may conclude that turnover has no impact on performance when actually both positive and negative effects of turnover are at work.

While the performance dispersion of high turnover funds suggests the likelihood of heterogeneous turnover effects on performance, a more interesting question is whether we can identify, based on ex ante information, which funds are likely to benefit from and which funds are likely to suffer from high turnover. We find that past fund performance offers a simple yet power clue. The intuition is as follows. First, for a given fund, turnover is a relatively stable fund characteristic over time. And further, for a given fund, if the effect of turnover on the performance is also stable over time (despite being heterogenous across funds), then how turnover affects fund performance in the past is indicative of the turnover-performance relation in the future. This intuition translates into an empirical hypothesis that turnover has a positive impact on fund performance persistence – among funds with higher turnover, past performance is a stronger indicator of future performance. This hypothesis is visualized in Figure 3.2. Here, we continue to consider the four funds discussed in the previous example but extend the setting to two periods. Among the two high-turnover funds, Fund D persistently benefits from aggressive response to investment opportunities while Fund D persistently suffers from high trading costs at both periods. Thus there is a strong performance persistence between these two funds. Among the two low-turnover funds, Fund A also persistently benefits from investment opportunities and Fund C also persistently suffers from trading costs at both periods. However, due to low turnover, neither the positive or negative effect of turnover makes a big impact on performance. Thus performance persistence appears weaker between these two funds.

We find empirical evidence consistent with this hypothesis. Specifically, we double sort funds by both turnover and past performance (measured by the four-factor fund alpha). Among funds in the highest turnover quintile, those ranked in the top past-alpha quintile significantly outperform those ranked in the bottom past-alpha quintile by 0.333% per month, in terms of four-factor alphas. By contrast, among funds in the lowest turnover quintile, the difference in four factor alpha between the top and bottom past-alpha fund quintiles is much lower, at 0.157% per month.

Interestingly, the impact of turnover on fund performance is most visible among the funds with poor past performance. For funds in the lowest past-alpha quintile, those in the highest turnover quintile delivers a negative four-factor alpha of -0.241% per month, significantly below the four-factor alpha of funds in the lowest turnover quintile (-0.115% per month). This finding is consistent with the notion that funds with low past alphas do not benefit substantially from trading on short-term investment opportunities; rather, the main effect of high turnover is high trading cost. Thus, among the funds with low past alpha, turnover has a persistently negative impact on performance. Further, among funds in the highest quintile of past alphas, performance is positively correlated with turnover, but the difference in four-factor alpha between the top and bottom turnover quintiles is not statistically significant.[2] For these funds, it appears that the positive effect of trading on available investment opportunities and the negative impact of high trading cost balance each other in affecting performance.

The effect of portfolio turnover on fund performance persistence is further confirmed using Fama-MacBeth multivariate regression analysis, where we control for the effect of various fund characteristics, such as fund size, age, expense ratio, fund return volatility. We also control for the effect of fund activeness, based on the Active Share of Cremers and Petajisto (2009), and the R-square of Amihud and Goyenko (2013).

Our analysis also helps resolve an inference issue noted by Pastor, Stambaugh, and Taylor (2017). Because turnover and performance are measured at two sequential time periods, a positive cross-sectional relation between turnover and subsequent performance does not necessarily mean that higher-turnover funds enjoy better performance after taking into account the higher trading costs they may incur during the period when turnover is measured. Our findings suggest that performance is either persistently lower (for low-past-alpha funds) or persistently higher (for high-past-alpha funds) during the two sequential periods that include the period of measuring fund turnover. Such inference, based on performance persistence, does not suffer from the asynchronous measurement of trading cost and performance, and thus presents a clear picture of the performance impact of turnover.

Pastor, Stambaugh, and Taylor (2017) also raise an interesting point that the relation between turnover and performance may be more visible in the time series of a given fund,

[2]In the entire sample, among the funds in the highest past-alpha quintile, the four-factor alpha of funds in the top turnover quintiles is 0.092% per month, positive but insignificant. However, in an alternative fund sample restricted to funds with a modestly long history of return records, the corresponding four-factor alpha for the high-past-alpha and high-turnover funds is significantly positive, at 0.126%. This suggests that some high-turnover funds do manage to deliver superior performance.

rather across funds. Empirically, they report a strong positive time-series turnover-performance relation, but a weak cross-sectional relation. We perform further analysis to evaluate the time series dimension versus the cross-sectional dimension of the effect of turnover on performance persistence. For this purpose, we perform panel regressions of fund performance on past alphas, turnover, and the interaction term of past alpha and turnover that intends to capture the effect of turnover on performance persistence. The panel regressions use fund-fixed effects to control the cross-sectional turnover-performance relation (as well as time-fixed effects). However, by including past fund alpha as an explanatory variable, we are dealing with a dynamic panel model with fixed effects. Due to the presence of both the fund-fixed effects and the lagged fund performance, in finite-sample the coefficients and error terms are correlated, causing potential inference biases (Nickell 1981). In this paper, we use a bootstrap approach to address potential biases in our fixed-effects dynamic panel regressions.[3] The regression results show that fund turnover is significantly positively related to subsequent performance, confirming the finding of Pastor, et al. (2017). On the other hand, the interaction between turnover and past alpha has an insignificant coefficient. Thus, the impact of turnover on performance persistence is not a time-series effect, but largely a cross-sectional effect.

To sum up, we contribute to the mutual fund literature by identifying heterogenous effects of portfolio turnover on fund performance. Such heterogeneity shows up in the

[3] The popular method to deal with dynamic panel regressions with fixed effects is to include lagged level and change of dependent variables as instruments; e.g., Arellano and Bond (1991) and Blundell and Bond (1998). However, lagged fund alphas are only weakly correlated with future alphas and thus they may suffer from the weak-instrument problem. This motivates us to adopt a bootstrap approach, where estimated coefficients and their corresponding t-statistics are compared with bootstrapped distributions of the coefficients and t-statistics to make statistical inference. The bootstrapping procedure we adopt ensures that the bootstrapped distributions of coefficients and t-statistics are generated under bootstrapped samples that retain the fund-fixed effects and the correlation structure of the residuals of the original sample.

relatively wide dispersion of performance among high turnover funds, as well as in the effect of fund turnover on performance persistence. To our knowledge, this is the first study to document a significantly positive effect of portfolio turnover on performance persistence. In addition, we find that the relation between turnover and performance persistence is largely a cross-sectional effect, not a time-series effect. In reaching this conclusion, we resort to a bootstrap approach to address potential biases associated with dynamic panel model with fixed effects.

The rest of the paper is organized as follows. Section 3.2 describes our sample and variable construction. Section 3.3 presents our empirical evidence on the cross-sectional relation between turnover and performance persistence. Section 3.4 tests the time-series relation between turnover and performance persistence, discusses the dynamic panel bias embedded in our specification and how we employ the bootstrap approach to address the bias. Section 3.5 concludes.

3.2 Data and Variable Description

3.2.1 Sample Construction

We obtain a large sample of mutual funds from the survivor-bias-free US mutual fund database maintained by the Center for Research of Security Prices (CRSP). The original sample of mutual funds from CRSP is further processed in the following way. First, we identify US domestic equity funds using the investment objective code provided by CRSP.[4]

[4] In CRSP, US equity funds are identified by the variable "CRSP_OBJ_CD" having a value of "ED". However, this variable may have missing values. If the value of this variable is missing for a given fund in a given year, we consider the fund to be a domestic equity fund as long as its most recent non-missing value for CRSP_OBJ_CD is "ED".

Second, following the convention of the existing literature (e.g., Pastor, Stamburgh, and Taylor (2015; 2017), we further exclude index funds, ETFs, and sector funds using indicators from CRSP. Third, many mutual funds have multiple share classes, and the CRSP mutual fund database provides fund data at share class level. For the different share classes of the same fund, many key characteristics of interest, such as portfolio turnover, are the same or very similar. Therefore we aggregate the share class level data to the fund level.[5] Finally, to avoid the incubation bias (Evans (2010)), we also eliminate fund-month observations if the observations are prior to the fund organization date or if the reported Total Net Assets (TNA) is less than $10 million. Our final sample has 5,889 unique funds between 1980 and 2016.

We extract from CRSP monthly fund net returns, portfolio turnover ratios, annual expense ratios, TNA and first offer date. As discussed above, since CRSP reports fund characteristics are at the share class level, we aggregate them into the fund level. TNA is the sum of share-class level TNA. Monthly fund net returns, portfolio turnover ratios, and annual expense ratios are value-weighted at the fund level. Fund age is calculated using the first offer date of the oldest share class of a fund.

Part of our analysis involves bootstrapping. In order to implement the bootstrap procedure, we also construct a restricted sample. Specifically, following Barras, Scaillet, and Wermers (2010) and Fama and French (2010), we require funds in the restricted sample to have at least 60 months of net returns. This results in a sample of 2,758 unique funds between 1980 and 2016.

[5] We use both the variable CRSP_CL_GRP provided by CRSP and the mapping provided by the MFLINK database (for funds with reported holdings in the Thomson Reuters database) to identify share classes of the same fund.

3.2.2 Turnover Measure

We use the portfolio turnover ratio reported in the CRSP database, which measures how often mutual funds actually trade.[6] Turnover ratio (TURN) is a fund's minimum of total securities sold or purchased, divided by its average Total Net Assets (TNA), over a given period (e.g. during a year):

$$TURN = \frac{min(\$buy, \$sell)}{avg(\$TNA)} \tag{1}$$

where the numerator is the minimum of the fund's total purchases ($buy) and sales ($sell) during a fiscal year, and the denominator is the fund's average total net asset value ($TNA) over the same period. Following Pastor, Stambaugh, and Taylor (2017), we winsorize TURN at the 1st and 99th percentiles in the entire sample.

3.2.3 Activeness Measures

We include several fund characteristics in our analysis. In addition to fund turnover, we also consider fund TNA, fund age, and expense ratio. Further, we include the standard deviation of the residuals from regressing funds' excess returns on Fama-French-Carhart four factors. It measures the idiosyncratic volatility of funds' past returns. Jordan and Riley (2015) find that funds' past return volatility is a strong predictor of future abnormal returns. Finally, we include two fund activeness measures. The mutual fund literature find that activeness measures help predict future fund performance. The most notable ones include Activeshare

[6] The benefit of using the reported turnover ratio is that it is readily available. Registered investment companies are required by the Investment Company Act of 1940 and the Securities Exchange Act of 1934 to disclose their turnover ratios in the NSAR form.

of Cremers and Petajisto (2009) and R2 of Amihud and Goyenko (2013). Activeshare equals half of the sum of the absolute differences between the fund weights and the corresponding benchmark weights. The higher the Activeshare, the larger deviation of fund portfolio is against its benchmark portfolio.[7] R2 is the R-square from regressing the past 24-month excess returns on the Fama-French-Carhart four factors. The lower the R2, the more active the fund is.

3.2.4 Descriptive Statistics

We first report descriptive statistics for both the full sample and restricted sample. Table 3.1 shows, for each sample year, the number of unique funds in our full sample, as well as characteristics of these funds at the mean and median. The number of funds breaks the 1,000 threshold at around 1993 and has been growing ever since. The growth slows down during the 2000s mainly due to the popularity of passive investment vehicles, such as ETFs and index funds. Comparison of the average TNA and the median TNA reveals a story that the fund industry is right skewed in terms of size. The average TNA at the end of 2016 was $1.7 billion while the median TNA was only $288 million. Clearly some mutual funds have a huge amount of assets under management. The average turnover ratio has been under 100% for most of years between 1980 and 2016, other than in the years of 2000 and 2001, which coincide with the tech bubble period. The median turnover ratio is close to the average turnover ratio. Table 3.2 shows the same statistics as in Table 3.1, for the restricted sample, which requires funds to have at least 60 months of net returns. A notable difference in terms of number of funds between the two samples is in the years after 2010.

[7]The Activeshare data between 1980 and 2015 is available on Martijn Cremers' website: http://activeshare.nd.edu.

The full sample has a lot more funds after 2010 than the restricted sample. One explanation is that there have been a slew of new funds created after the Great Recession. Since our sample ends in 2016, many of these funds are not likely to meet the five-year life restriction. However, as shown later in our analysis, the exclusion of these relatively young funds do not substantially change our key results. For the restricted sample, again the TNA distribution is right skewed.

In Table 3.3, we calculate average fund characteristics for each quintile rank-sorted by portfolio turnover ratio. At each month end, we rank-sort funds into quintiles based on their previous year end's reported turnover ratios. We then calculate the time-series average of each fund characteristics for the entire time period between 1980 and 2016. Quintile 1 represents the group of funds with the lowest turnover ratio at the end of each month, while Quintile 5 represents the group of funds with the highest turnover ratio at the end of each month. Average turnover ratio of the lowest turnover quintile is 0.16, and that of the highest turnover quintile is 2.01. Thus the turnover dispersion across funds is substantial. Fund age is calculated as the months between January 1980 and the earliest first offer date of all share classes within the same fund and. Higher-turnover funds tend to be older, with the average age of the lowest turnover quintile being 18.8 months versus 14.5 months of the highest turnover quintile. Higher-turnover funds also tend to be smaller in size. Funds in the lowest turnover quintile have on average \$1.597 billion assets under management, while those in the highest turnover quintile have only \$580 million assets under management. Higher-turnover funds charge higher fees than lower turnover funds, with the highest turnover quintile charging 1.32% on an annual basis versus 1.04% for the lowest turnover quintile. There is also a relation between turnover and fund activeness, as measured by Activeshare and

R2. Funds in the lowest turnover quintile have the lowest Activeshare (0.8271) and the highest R2 (0.8919). STDDEV is the standard deviation of residuals from the time-series regression of fund excess returns on Fama-French-Carhart four factors. Higher STDDEV indicates higher idiosyncratic volatility in fund returns. Funds in the highest turnover quintile have the highest STDDEV (0.0152) compared to those in the lowest turnover quintile (0.0117).

3.3 Cross-Sectional Relation between Turnover and Performance Persistence

In this section, we look at whether turnover predicts future fund performance and has an impact on performance persistence. Table 3.3 shows that turnover ratio is closely related to other activeness measures, such as Activeshare and R2. Cremers and Petajisto (2009) shows that funds with higher Activeshare outperform funds with lower Activeshare in the future. Amihud and Goyenko (2013) also shows that funds with lower R2 outperform funds with higher R2 in the future. But these activeness measures do not necessarily measure funds' trading activities. They may only indicate a large deviation of fund portfolio holdings from benchmark indexes. On the other hand, turnover ratio measures funds' trading activities. The motivation behind funds' trading activities could be both information driven or liquidity driven, both manifestation of investment skills. Indeed, Chen, Jegadeesh, and Wermers (2000) suggest two competing hypotheses in explaining the relation between turnover and performance. The first hypothesis is that if managers hold better information and have the ability to target profitable investments, they are likely to trade more. Managers who don't have better information are likely to trade less in order not to incur trading costs. This hypothesis suggests a positive relation between turnover and performance. The second hypothesis suggests that some fund managers who trade frequently rely on noisy information or give the impression of active management. Based on this hypothesis, we would expect there is no positive relation between turnover and performance or even negative relation between turnover and performance. In the following, we will test the first hypothesis that fund managers trade frequently due to their informational advantage and only managers with true skills can outperform in the future, which is our performance persistence hypothesis.

3.3.1 Performance of Fund Portfolios Sorted by Turnover Ratio

We first perform simple single sort by turnover ratio. At the end of each month, we sort funds into five quintiles based on previous year's reported turnover ratio. We then calculate the equal-weighted net returns of these quintile portfolios over the next month. Repeating this procedure across all months yields time series of monthly returns on each quintile portfolio. Next, we calculate the returns of the high-minus-low portfolio that is the difference between returns of the highest turnover quintile portfolio and the lowest turnover quintile portfolio. Finally, we regress the time-series returns of the five quintile portfolios and the high-minus-low portfolio on the Fama-French-Carhart four factors

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \epsilon_{i,t}, \quad (2)$$

where $R_{i,t}$ is quintile portfolio i's net return in month t and $R_{f,t}$ is the monthly T-bill rate in month t. MKT is the return difference between the market portfolio and the monthly T-bill rate. SMB is the return difference between the factor-mimicking portfolios for small minus big capitalization. HML is the return difference between the factor-mimicking portfolios for high minus low book-to-market firms. MOM is the return difference between the factor-mimicking portfolios for high minus low momentum firms.[8] α_i is the risk-adjusted returns for quintile portfolio i.

Table 3.4 reports the simple single sort results for turnover ratio. The lowest turnover quintile predicts a negative 5 bps risk-adjusted next-month return that is weakly significant (t=-1.82). The highest turnover quintile predicts a even worse risk-adjusted return of -10.5 bps (t=-2.55). But the return difference between the top and bottom turnover quintile has an insignificant alpha (t=-1.24).

Table 3.4 also shows the return dispersion for each turnover quintile. Return dispersion measures the standard deviation of returns of each quintile portfolios, averaged across all months. The top turnover quintile has a higher return dispersion (4.68) than the bottom quintile (4.05).

3.3.2 Performance of Fund Portfolios Double Sorted by Past Performance and Turnover Ratio

In this section, we sort funds by both past α and turnover, and see whether past α and turnover jointly affect fund performance. The double-sort analysis may potentially sharpen the single-sort result as we can separate fund managers into groups who trade on useful information and who trade on noisy information. For example, fund managers who exhibit skills and trade frequently are more likely to trade on useful information thus will outper-

[8]MKT, SMB, HML, and MOM factor-mimicking portfolio returns could be found on Ken French's website.

form fund managers who don't exhibit skills and trade on noisy information.

Again, fund past α is estimated by regressing each fund's past 24-month net returns on Fama-French-Carhart four factors. At the end of each month, we sort funds into 5 by 5 of total 25 portfolios, *independently*, by estimated α and previous year's reported turnover ratio. We then calculate the equal-weighted net returns of these 25 portfolios over the next month. Repeating this procedure across all months yields time series of monthly returns on each of the 25 portfolio. Next, we calculate the returns of the high-minus-low portfolio respectively for each of the 5 quintiles by estimated α and turnover ratio. This yields five high-minus-low portfolios for estimated α quintiles and five high-minus-low portfolios for turnover quintiles. Finally, we regress the time-series returns of all these portfolios (36 portfolios) on the Fama-French-Carhart four factors using Equation (2). We repeat this procedure for both the full sample and restricted sample.

Panel A of Table 3.5 shows the double-sort results for the full sample. The results confirm our hypothesis that only skilled managers can target profitable trading opportunities. Within the lowest past α quintile, across all turnover quintiles, the next month risk-adjusted returns are negative and significant. The portfolio with the lowest past α as well as the highest turnover delivers a negative 24 bps and is highly significant (t=-4.59). This confirms our hypothesis that unskilled managers often trade on noisy information and thus underperform. The high-minus-low turnover portfolio within the lowest past α quintile is a negative 12 bps (t=-2.39). On the other hand, within the highest past α quintile, almost all turnover quintiles predict positive next month risk-adjusted returns. The portfolio with the highest past α and the highest turnover predicts a positive 9 bps risk-adjusted return (t=1.34). And the high-minus-low portfolio in terms of past α within the highest turnover quintile predicts a 33 bps risk-adjusted return and is highly significant (t=4.39). The overall trend of high-minus-low portfolios across all turnover quintiles exhibits a monotonic increasing order, from 15.7 bps to 33.3 bps. The difference between the portfolio with the highest past α and the highest turnover and the portfolio with the lowest past α and the lowest turnover is a statistically significant 17.7 bps (t=2.63). So it is clear that skilled fund managers do take advantage of better information and trade more frequently.

Panel B of Table 3.5 shows the double-sort results for the restricted sample, where we require funds to have at least 60 months net returns. The overall pattern of the results is similar to Panel A. The unskilled managers are unlikely to trade frequently on better information thus deliver negative risk-adjusted returns in the next month. For example, the portfolio with the lowest past α and the highest turnover predicts a negative 20 bps risk-adjusted return (t=-3.97). On the other hand, the skilled managers continue to deliver positive risk-adjusted returns. Particularly, the portfolio with the highest past α and the highest turnover predicts a positive and significant 12.6 bps risk-adjusted return (t=1.89). The difference between the portfolio with the highest past α and the highest turnover and the portfolio with the lowest past α and the lowest turnover is a statistically significant 15.3 bps (t=2.37).

3.3.3 Multivariate Regression

As shown in Table 3.3, turnover is correlated with other fund characteristics. Funds with higher turnover ratio tend to be younger, smaller, and more active (with higher Activeshare and lower R2). We perform Fama-MacBeth cross-sectional regression to control for the effects of these fund characteristics and single out the effect of turnover on fund performance persistence. The depend variable for the regression is the four-factor adjusted return, computed in the following way. At the end of each month t, we obtain Fama-French-Carhart four factor loadings by regressing each fund j's past 24-month excess returns on MKT, SMB, HML, and MOM factors. The factor loadings are denoted $\hat{\beta}_{j,MKT,t}$, $\hat{\beta}_{j,SMB,t}$, $\hat{\beta}_{j,HML,t}$, and $\hat{\beta}_{j,MOM,t}$. We then compute next month's predicted return by multiplying the factor loadings by next month's factor returns. Finally, we subtract predicted returns from the observed excess returns to get the four-factor adjusted return as:

$$\begin{aligned}\hat{\alpha}_{j,t+1} = r_{j,t+1} - r_{f,t+1} - (\hat{\beta}_{j,MKT,t}\text{MKT}_{t+1} + \hat{\beta}_{j,SMB,t}\text{SMB}_{t+1} + \hat{\beta}_{j,HML,t}\text{HML}_{t+1} \\ + \hat{\beta}_{j,MOM,t}\text{MOM}_{t+1})\end{aligned}, \quad (3)$$

where $\hat{\alpha}_{j,t+1}$ is the predicted excess return for month $t+1$.

To test the effect of turnover on fund performance persistence, we run the following cross-sectional regression at each month end

$$\begin{aligned}\hat{\alpha}_{j,t+1} = a_0 + a_1\hat{\alpha}_{j,t} + a_2 Turnover_{j,t} + a_3\hat{\alpha}_{j,t} * Turnover_{j,t} + a_4 Log(TNA)_{j,t} + a_5 Fee_{j,t} \\ + a_6 Activeshare_{j,t} + a_7 R2_{j,t} + a_8 STDDEV_{j,t} + \epsilon_{j,t+1}\end{aligned}, \quad (4)$$

where $\hat{\alpha}_{j,t}$ is the estimated four-factor adjusted return in the previous month t. $Turnover_{j,t}$ is the reported turnover ratio closet to month t. $\hat{\alpha}_{j,t} * Turnover_{j,t}$ is the interaction term used to test the effect of turnover on fund performance persistence. $Log(TNA)_{j,t}$ is the natural log of fund TNA at month t. $Fee_{j,t}$ is the reported annual expense ratio closest to month t. $Activeshare_{j,t}$ is the Activeshare measure per Cremers and Petajisto (2009).[9] $R2_{j,t}$ is

[9] Activeshare measure is only available between 1980 and 2015.

calculated per Amihud and Goyenko (2013) by regressing each fund's past 24-month excess returns on Fama-French-Carhart four factors. $STDDEV_{j,t}$ is the standard deviation of residuals from the regression of each fund's past 24-month excess returns on Fama-French-Carhart four factors. It measures the idiosyncratic volatility of each fund's returns. There are total 440 months between 1980 and 2016. Thus we perform 440 Fama-MacBeth cross-sectional regression at the end of each month. We then calculate the time-series mean and t stats of the coefficients from equation (4). We repeat this procedure for both the full sample and the reduced sample where we require each fund to have at least 60 months returns.

Panel A of Table 3.6 shows the results for the full sample. There are seven regression specifications. Specification [1] shows that turnover alone doesn't predict fund performance (t=0.05), which is consistent with our single-sort result in Table 3.3. Specification [2] adds the interaction term of turnover and past α. The coefficient of past α is positive and significant (t=5.21). But our interest is in the coefficient of the interaction term of turnover and past α, which is a positive and significant 0.0497 (t=2.56). This result is consistent with our double-sort result by turnover and past α shown in Table 3.4. Specification [3] adds two more fund characteristic variables, fund size and fund fee. As shown in Table 3.3, smaller funds and more expensive funds trade more frequently than larger funds and cheaper funds. This makes sense as smaller funds are nimbler in the sense of incurring smaller trading costs. Funds charging higher fees often boast their active management skills thus tend to seek out more profit opportunities and act on them. So our question is whether these fund characteristics will dilute the effect of turnover on performance persistence. The coefficient of fund size is a negative and significant -0.0002 (t=-2.81), which means large funds tend to underperform their smaller peers. Surprisingly, the coefficient of fund fee is also negative and significant (t=-3.44), which indicates that more expensive funds are not necessarily as they advertised. Nonetheless, the effect of turnover is not diluted by these two fund characteristics. The coefficient of the interaction term of turnover and past α is almost the same as not adding the two fund characteristics. And the statistical significance remains (t=2.40). In specification [4], we further add three activeness measures, Activeshare, R2, and idiosyncratic volatility. Although the coefficients of Activeshare and R2 show the expected signs (positive for Activeshare and negative for R2), they are not statistically significant. While the coefficient of idiosyncratic volatility is a negative and significant -0.1007 (t=-2.51), which means funds with more volatile returns underperform their peers. Controlling for all these fund characteristics and activeness measures doesn't change the effect of the interaction term of turnover and past α. The coefficient of the interaction term of turnover and past α is a positive and significant 0.0511 (t=2.62). Cremers and Pareek (2016) argue that patient funds with high activeshare outperform. Thus in specification [5] we add an interaction term between turnover and activeshare. It turns out that neither activeshare nor the interaction term is significant. We also interact turnover with R2 in specification [6] but it doesn't seem it has any predictive power on future performance. Specification [7] includes all variables and the effect of turnover on performance persistence is still positive and significant.

We repeat the same procedure on the restricted sample. Panel B of Table 3.6 shows the same four specifications on the reduced sample. The pattern of the results are largely unchanged. The positive and significant coefficient on the interaction term of the turnover and past α are preserved across all four specification. The magnitude of the coefficients and t stats also remain very close to those in the full sample.

3.4 Time-Series Relation, Dynamic Panel Bias, and Bootstrapping

Pastor, Stambaugh, and Taylor (2017) show that there is a strong, within-fund, time-series relation between turnover and performance. Following their results, we test whether there is within-fund time-series effect of turnover on performance persistence. In the time series, our panel regression is essentially a dynamic panel regression that regresses future fund performance on lagged fund performance. When there is latent fund fixed effect, the dynamic panel model has an endogeneity problem. Removing fund fixed effect does not solve the endogeneity problem. We will discuss the dynamic panel bias and how to use bootstrapping to address it.

3.4.1 Time-Series Relation between Turnover and Performance Persistence

As shown in the previous section, the Fama-MacBeth regression results show a strong cross-sectional relation between turnover and performance persistence. Would this relation also exist over time within the same funds? In this section, we follow Pastor, Stambaugh, and Taylor (2017) and examine the time-series relation between turnover and performance persistence.

One way to test the time-series relation is to run within-fund time-series regression

$$\begin{aligned}\hat{\alpha}_{i,t+1} = a_i + b_{i,1}\hat{\alpha}_{i,t} + b_{i,2}Turnover_{i,t} + b_{i,3}\hat{\alpha}_{i,t} * Turnover_{i,t} + b_{i,4}Log(TNA)_{i,t} + b_{i,5}Fee_{i,t}&,\\ +b_{i,6}Activeshare_{i,t} + b_{i,7}R2_{i,t} + b_{i,8}STDDEV_{i,t} + \epsilon_{i,t+1}&\end{aligned} \tag{5}$$

where definition of each variable is the same as in equation (4). Only difference is that coefficients are fund specific. E.g., $b_{i,3}$ is the effect of the interaction between turnover and past α on next month risk-adjusted return for fund i. Here, our interest is how many $\hat{b}_{i,3}$ are greater than 0 and statistically significant. A positive $\hat{b}_{i,3}$ indicates that skilled managers take advantage of profitable investment opportunities and trade frequently to improve their risk-adjusted return next month. But due to individual funds' relatively short track record, the coefficient estimates tend to be noisy.

To increase the power of our estimation, we pool all funds together and run the fixed-effect panel regression imposing the following restriction

$$b_{1,j} = b_{2,j} = b_{3.j} = ... = b_j, \tag{6}$$

where $b_{1,j}$ is the jth coefficient of regression setting in (5) for fund 1, $b_{2,j}$ is the jth coefficient of regression setting in (5) for fund 2, and so on. The pooled regression setting is

$$\begin{aligned}\hat{\alpha}_{i,t+1} = a_i + a_t + b_1\hat{\alpha}_{i,t} + b_2 Turnover_{i,t} + b_3\hat{\alpha}_{i,t} * Turnover_{i,t} + b_4 Log(TNA)_{i,t} + b_5 Fee_{i,t} \\ + b_6 Activeshare_{i,t} + b_7 R2_{i,t} + b_8 STDDEV_{i,t} + \epsilon_{i,t+1}\end{aligned}, \tag{7}$$

where a_i is the fund-fixed effect when condition (6) is imposed on all funds. We also control for month-fixed effects, a_t. The coefficient estimates in equation (7) now reflect the time-series relation between various fund characteristics and next month risk-adjusted return.

As noted in Petersen (2009), when running panel regression, standard errors are biased if residuals are correlated across observations. One remedy is to correct the standard errors by clustering. We consider two variations of clustering for our panel regression. One is clustering by fund category and time, as used in Paster, Stambaugh, and Taylor (2016).

The other is clustering by fund and time. Our definition of fund category is different from Pastor, Stambaugh, and Taylor (2016)'s. Pastor et. al. use Morningstar size and style categories, such as large versus small and growth versus value. Since we don't have access to Morningstar data, instead we rely on style defined by CRSP survivor-bias-free US Mutual Fund database.[10]

Table 3.7 shows results of fixed-effect panel regression. The first three specifications are clustered by fund category and time (month). Consistent with the findings in Pastor, Stambaugh, and Taylor (2017), even with a different definition of fund category, the pooled panel regression shows a strong relation between turnover and next month risk-adjusted return. And the performance persistence also remains, with the coefficient of the interaction between turnover and past α being positive (0.025971) and statistically significant (t=2.48), after controlling for other fund characteristics and activeness measures. Surprisingly, specifications [4], [5], and [6], clustered by fund and time (month), tells a different story. The strong relation between turnover and performance, as well as the performance persistence, no longer exist (t=1.02).

[10]CRSP_CD_OBJ field in FUND_STYLE dataset sources fund objective code from Wiesenberger between 1962 and 1993, from Strategic Insight between 1993 and 1998, and from Lipper since 1998. Examples of CRSP_CD_OBJ values are 'EDCL' (large cap), 'EDCS' (small cap), 'EDYG' (growth), and 'EDYI' (income).

3.4.2 Dynamic Panel Bias

The data generating process in Equation (7) is essentially a dynamic panel taking the form of the following general model:

$$y_{i,t} = \alpha y_{i,t-1} + \mathbf{X}'_{i,t-1}\beta + \epsilon_{i,t}$$
$$\epsilon_{i,t} = \mu_i + v_{i,t}. \tag{8}$$
$$E(\mu_i) = E(v_{i,t}) = E(\mu_i v_{i,t}) = 0$$

If we apply classical OLS to Equation (8), there is a "dynamic panel bias" (Nickell (1981)) because $y_{i,t-1}$ is correlated with the fixed effect μ_i in the error term $\epsilon_{i,t}$. There are basically two ways to deal with the dynamic panel bias. One is to transform the data to remove the fixed effect. The other is to instrument $y_{i,t-1}$ with variables thought uncorrelated with the fixed effect. We apply the first method using mean-deviation transformation. But within-groups does not eliminate dynamic panel bias entirely (Bond (2002)). In the within-group transformation, the lagged dependent variable becomes $y^*_{i,t-1} = y_{i,t-1} - \{1/(T-1)\}(y_{i2} + \cdots + y_{iT})$, where the error term becomes $v^*_{i,t} = v_{i,t} - \{1/(T-1)\}(v_{i2} + \cdots + v_{iT})$. The issue here is that the $y_{i,t-1}$ term in $y^*_{i,t-1}$ correlates with the $-\{1/(T-1)\}v_{i,t-1}$ term in $v^*_{i,t}$, and the $-\{1/(T-1)\}y_{i,t}$ correlates with the v_{it} term. So the endogeneity problem persists. Using lagged $y_{i,t-1}$ to instrument for $y^*_{i,t-1}$ wouldn't work because it is also correlated with the transformed error $v^*_{i,t}$. But if T were large, then the $-\{1/(T-1)\}v_{i,t-1}$ and $-\{1/(T-1)\}y_{i,t}$ terms would be insignificant so the dynamic panel bias would disappear. The T in our mutual fund sample is considered large because the data is of monthly frequency. So we don't have to apply the methods proposed by AB (Arellano and Bond (1991)) and

BB (Blundell and Bond (1998)) to address the dynamic panel bias. Nonetheless, we run bootstrapping to confirm this.

3.4.3 Bootstrapping

Kosowski, Timmermann, Wermers, and White (2006) and Fama and French (2010) propose to use bootstrap to evaluate mutual fund performance due to non-normal distribution of individual fund returns. The possible causes are that the residuals of fund returns are not drawn from a multivariate normal distribution, or correlations in these residuals are not zero, or funds have different risk levels, or parameter estimation error results in the standard critical values of the normal distribution being inappropriate in the cross section. The solution is to perform bootstrap to improve inference.

We follow the procedure in Kosowski, Timmermann, Wermers, and White (2006) and Fama and French (2010) to build the sample for our bootstrap procedure. From 1980 to 2016, we require funds in our bootstrap sample to have at least 60 months return. These returns don't have to be adjacent.

We bootstrap under both the alternative and the null. When bootstrapping under the alternative, for each fund i, we first calculate the estimated residual

$$\begin{aligned}\hat{\epsilon}_{i,t+1} = \hat{\alpha}_{i,t+1} - \{\hat{a}_i + \hat{a}_t + \hat{b}_1\hat{\alpha}_{i,t} + \hat{b}_2 Turnover_{i,t} + \hat{b}_3\hat{\alpha}_{i,t} * Turnover_{i,t} \\ +\hat{b}_4 Log(TNA)_{i,t} + \hat{b}_5 Fee_{i,t} + \hat{b}_6 Activeshare_{i,t}, \\ +\hat{b}_7 R2_{i,t} + \hat{b}_8 STDDEV_{i,t}\}\end{aligned} \tag{9}$$

where $\hat{a}_i$, $\hat{a}_t$, $\hat{b}_1$, $\hat{b}_2$, $\hat{b}_3$, $\hat{b}_4$, $\hat{b}_5$, $\hat{b}_6$, $\hat{b}_7$, and $\hat{b}_8$ are estimated from Equation (7). In each simulation, for each fund month, we randomly draw with replacement from $\hat{\epsilon}_{i,t+1}$ to simulate $\hat{\alpha}^*_{i,t+1}$. We repeat this procedure for each fund but eliminate funds with less then 8 fund-month observations (Fama and French (2010)). We then re-run Equation (7) using $\hat{\alpha}^*_{i,t+1}$ as dependent variable. We repeat the simulation 2,000 times and obtain a distribution of $\tilde{b}_3$ and t stats.

When bootstrapping under the null, we modify Equation (7) and run

$$\begin{aligned}\hat{\alpha}_{i,t+1} = a_i + a_t + b_1\hat{\alpha}_{i,t} + b_2Turnover_{i,t} + b_4Log(TNA)_{i,t} + b_5Fee_{i,t} \\ +b_6Activeshare_{i,t} + b_7R2_{i,t} + b_8STDDEV_{i,t} + \epsilon_{i,t+1}\end{aligned}, \quad (10)$$

where b_3 is assumed to equal 0. We then calculate the estimated residual

$$\begin{aligned}\hat{\epsilon}_{i,t+1} = \hat{\alpha}_{i,t+1} - \{\hat{a}_i + \hat{a}_t + \hat{b}_1\hat{\alpha}_{i,t} + \hat{b}_2Turnover_{i,t} + \hat{b}_4Log(TNA)_{i,t} + \hat{b}_5Fee_{i,t} \\ +\hat{b}_6Activeshare_{i,t} + \hat{b}_7R2_{i,t} + \hat{b}_8STDDEV_{i,t}\}\end{aligned}, \quad (11)$$

where $\hat{a}_i$, $\hat{a}_t$, $\hat{b}_1$, $\hat{b}_2$, $\hat{b}_4$, $\hat{b}_5$, $\hat{b}_6$, $\hat{b}_7$, and $\hat{b}_8$ are estimated from Equation (10). In each simulation, for each fund month, we randomly draw with replacement from $\hat{\epsilon}_{i,t+1}$ to simulate $\hat{\alpha}^*_{i,t+1}$. We repeat this procedure for each fund but eliminate funds with less then 8 fund-month observations (Fama and French (2010)). We then re-run Equation (7) using $\hat{\alpha}^*_{i,t+1}$ as dependent variable. We repeat the simulation 2,000 times and obtain a distribution of $\tilde{b}_3$ and t stats.

Table 3.8 reports results for both bootstrapping under the alternative and under the null. For bootstrapping under the alternative, the percentage of coefficients less than 0 for past α is 0, meaning that the bootstrapping confirms the predictive power of past performance on future performance as shown in our fixed-effect panel regression (Table 3.7). While the percentage of coefficients less than 0 for turnover is 0.0952, which weakly (at 10% level) confirms the time-series relation between turnover and performance. Finally, the percentage of coefficients less than 0 for the interaction between turnover and past α is 0.1324, which shows that the effect of turnover on performance persistence is not reliably time series, but rather cross sectional. Bootstrapping under the null on the effect of turnover on performance persistence confirms the results in the alternative hypothesis.

3.5 Conclusions

In this study, we examines the relation between mutual fund turnover and performance persistence. Mutual fund managers trade in response to profitable investment opportunities. We argue that only skilled fund managers are able to discern and target profitable trading opportunities and trade to their advantage. Unskilled fund managers trade on noisy information and eventually underperform. We find that the positive relation between fund turnover and performance persistence is largely cross sectional, not time series.

Table 3.1: Summary Statistics: Full Sample

This table summarizes U.S. domestic actively-managed equity mutual funds between 1980 and 2016. We report the number of funds at the end of each year. If fund data is not available at the end of the year, the nearest quarter end is reported. TNA is the total net asset reported by each fund at the end of each year. Turnover is the portfolio turnover ratio reported by each fund at the nearest fiscal year end.

Year	Number of Funds	Total TNA ($b)	Avg. TNA ($m)	Med. TNA (%)	Avg. Turnover (%)	Med. Turnover (%)
1980	272	46	169	64	75	55
1981	284	43	153	59	72	56
1982	294	54	185	77	78	52
1983	333	74	223	96	81	63
1984	362	78	215	84	74	60
1985	415	110	266	103	82	65
1986	499	149	298	93	82	68
1987	586	165	282	86	91	73
1988	630	181	287	80	78	61
1989	694	231	333	87	74	57
1990	749	225	301	76	84	58
1991	834	332	398	93	96	44
1992	931	433	465	110	75	55
1993	1,055	597	566	125	78	60
1994	1,160	676	583	123	79	59
1995	1,269	972	766	156	83	65
1996	1,442	1,294	897	164	85	66
1997	1,677	1,748	1,043	172	87	66
1998	1,926	2,144	1,113	164	88	68
1999	2,076	2,750	1,325	178	93	71
2000	2,225	2,683	1,206	170	102	79
2001	2,272	2,394	1,054	159	103	79
2002	2,277	1,899	834	125	99	72
2003	2,302	2,533	1,100	168	92	68
2004	2,314	2,926	1,264	192	83	64
2005	2,389	3,238	1,356	205	82	64
2006	2,442	3,713	1,520	225	81	63
2007	2,479	3,948	1,593	222	83	64
2008	3,218	2,743	852	135	95	72
2009	3,143	3,454	1,099	186	99	71
2010	3,080	3,844	1,248	225	89	62
2011	3,115	3,674	1,180	213	88	64
2012	3,058	3,946	1,290	231	81	54
2013	3,122	5,130	1,643	294	80	54
2014	3,150	5,411	1,718	304	78	52
2015	3,187	5,141	1,613	271	80	53
2016	3,177	5,326	1,676	288	100	61

Table 3.2: Summary Statistics: Bootstrap Sample

This table summarizes U.S. domestic actively-managed equity mutual funds between 1980 and 2016. In this bootstrap sample, we require each fund to have at least 60 months return, which doesn't have to be adjacent. We report the number of funds at the end of each year. If fund data is not available at the end of the year, the nearest quarter end is reported. TNA is the total net asset reported by each fund at the end of each year. Turnover is the portfolio turnover ratio reported by each fund at the nearest fiscal year end.

Year	Number of Funds	Total TNA ($b)	Avg. TNA ($m)	Med. TNA (%)	Avg. Turnover (%)	Med. Turnover (%)
1980	239	44	184	69	75	55
1981	253	42	165	65	71	56
1982	269	53	197	93	78	52
1983	303	72	239	111	81	63
1984	327	76	232	95	73	60
1985	381	107	281	107	80	63
1986	444	142	320	103	81	65
1987	511	156	304	93	90	71
1988	551	171	311	92	77	61
1989	605	221	365	99	73	57
1990	644	215	334	86	81	58
1991	722	317	440	111	107	59
1992	812	414	509	131	73	53
1993	921	575	625	158	76	59
1994	1,004	654	652	152	77	57
1995	1,105	946	856	182	81	63
1996	1,250	1,259	1,007	203	83	64
1997	1,437	1,699	1,182	205	85	65
1998	1,602	2,073	1,294	209	87	67
1999	1,708	2,620	1,534	235	91	71
2000	1,823	2,537	1,392	235	99	77
2001	1,893	2,241	1,184	211	99	78
2002	1,946	1,767	908	166	95	70
2003	2,013	2,408	1,196	212	89	67
2004	2,064	2,818	1,365	231	82	63
2005	2,124	3,094	1,457	241	81	63
2006	2,147	3,557	1,657	274	80	63
2007	2,146	3,781	1,762	288	80	62
2008	2,131	2,233	1,048	165	91	70
2009	2,091	2,845	1,360	216	96	69
2010	2,032	3,165	1,557	262	85	61
2011	1,973	2,961	1,501	274	82	63
2012	1,883	3,196	1,697	314	74	52
2013	1,810	4,131	2,282	442	71	51
2014	1,724	4,289	2,488	488	66	48
2015	1,698	4,044	2,382	467	65	48
2016	1,650	4,065	2,464	475	70	55

Table 3.3: Fund Characteristics

This table reports the average fund characteristics across turnover quintiles. In each month, we sort funds into quintile portfolios based on portfolio turnover ratio reported at the nearest fiscal year end. Age is the month difference between Jan 1980 and the earliest first offer date of a fund's all share classes. TNA is the total net asset aggregated at the fund level. Fee is the value-weighted expense ratio reported by fund share classes in the nearest fiscal year end. Activeshare is calculated per Cremers and Petajisto (2009). R2 is the R square from regressing funds past 24 months excess returns on the Fama-French-Carhart four factors. STDDEV is the standard deviation of residuals from regressing funds past 24 months excess returns on the Fama-French-Carhart four factors.

Turnover Rank	Turnover	Age	TNA	Fee	ActiveShare	R2	STDDEV
1-Low	0.16	18.8	1,597	0.0104	0.8271	0.8919	0.0117
2	0.63	16.9	1,318	0.0111	0.8382	0.8944	0.0121
3	0.97	16.9	884	0.0117	0.8376	0.8907	0.0129
4	1.58	15.8	687	0.0121	0.8413	0.8942	0.0136
5-High	2.01	14.5	580	0.0132	0.8660	0.8607	0.0152
High-Low	1.85	-4.3	-1,016	0.0028	0.0389	-0.0311	0.0035
t stat	(67.4)	(-9.89)	(-8.28)	(27.5)	(11.54)	(-7.05)	(9.73)

Table 3.4: Performance of Fund Portfolios Sorted by Turnover

This table reports the risk-adjusted returns of sorted fund portfolios. In each month, we sort funds into equal-weighted quintile portfolios based on portfolio turnover ratio. We report the after-expense four-factor alpha of each portfolio, the t stat associated with the alpha, and the average standard deviation of the net returns across funds in each portfolio.

	1-Low	2	3	4	5-High	High-Low
Alpha (%)	-0.050*	-0.091***	-0.104***	-0.118***	-0.105**	-0.055
t stat	(-1.82)	(-3.14)	(-3.10)	(-3.43)	(-2.55)	(-1.24)
Return Dispersion (%)	4.05	4.22	4.38	4.66	4.68	1.56

Table 3.5: Performance of Fund Portfolios Double-Sorted by Past Alpha and Turnover

This table reports performance of fund portfolios formed on monthly independent double-sorts by past alpha and turnover ratio. Past alpha are estimated from the Fama-French-Carhart four-factor model using rolling 24-month after-expense fund returns. Turnover ratio is as of the end of the nearest fiscal year end. Panel A reports the double-sort results for the full sample. Panel B reports the double-sort results for the bootstrap sample. t stat is reported in parenthesis.

Panel A: Full Sample

	Turnover					
Past Alpha	1-Low	2	3	4	5-High	High-Low
Low	-0.115**	-0.226***	-0.266***	-0.290***	-0.241***	-0.127**
	(-2.23)	(-4.31)	(-4.69)	(-5.20)	(-4.59)	(-2.39)
2	-0.119***	-0.129***	-0.141***	-0.104***	-0.157***	-0.039
	(-3.48)	(-3.66)	(-3.93)	(-2.70)	(-3.67)	(-0.92)
3	-0.026	-0.072**	-0.095***	-0.104***	-0.142***	-0.116**
	(-0.80)	(-2.24)	(-2.70)	(-2.73)	(-3.30)	(-2.40)
4	-0.072**	-0.063	-0.052	-0.067	-0.026	0.046
	(-2.01)	(-1.63)	(-1.32)	(-1.64)	(-0.52)	(0.83)
High	0.042	0.019	0.015	-0.007	0.092	0.050
	(0.92)	(0.40)	(0.28)	(-0.14)	(1.34)	(0.80)
High-Low	0.157**	0.245***	0.281***	0.282***	0.333***	0.177***
	(2.37)	(3.52)	(4.21)	(4.13)	(4.39)	(2.63)

Panel B: Bootstrap Sample

	Turnover					
Past Alpha	1-Low	2	3	4	5-High	High-Low
Low	-0.118**	-0.195***	-0.237***	-0.257***	-0.202***	-0.085
	(-2.27)	(-3.70)	(-4.10)	(-4.72)	(-3.97)	(-1.62)
2	-0.107***	-0.127***	-0.111***	-0.090**	-0.120***	-0.013
	(-3.15)	(-3.56)	(-3.12)	(-2.25)	(-2.70)	(-0.28)
3	-0.018	-0.060*	-0.075**	-0.096**	-0.124***	-0.106**
	(-0.51)	(-1.83)	(-2.17)	(-2.42)	(-2.88)	(-2.13)
4	-0.064*	-0.062	-0.042	-0.028	0.019	0.082
	(-1.77)	(-1.54)	(-1.05)	(-0.68)	(0.37)	(1.44)
High	0.057	0.044	0.045	-0.010	0.126*	0.068
	(1.26)	(0.91)	(0.84)	(-0.18)	(1.89)	(1.13)
High-Low	0.175***	0.238***	0.282***	0.247***	0.328***	0.153**
	(2.62)	(3.40)	(4.12)	(3.65)	(4.38)	(2.37)

Table 3.6: Fama-MacBeth Multivariate Regressions

This table reports results of Fama-MacBeth regressions that analyze the impact of turnover ratio on performance persistence. The dependent variable is the fund's month $t+1$ predicted excess return calculated as $\hat{\alpha}_{j,t+1} = r_{j,t+1} - r_{f,t+1} - (\hat{\beta}_{j,MKT,t}\text{MKT}_{t+1} + \hat{\beta}_{j,SMB,t}\text{SMB}_{t+1} + \hat{\beta}_{j,HML,t}\text{HML}_{t+1} + \hat{\beta}_{j,MOM,t}\text{MOM}_{t+1})$. All the independent variables are as of month t. Past α is the intercept of regressing past 24 month excess returns on Fama-French-Carhart four factors. Log(TNA) is the natural log of total net asset aggregated at the fund level. Fee is the value-weighted expense ratio reported by fund share classes in the nearest fiscal year end. Activeshare is calculated per Cremers and Petajisto (2009). R2 is the R square from regressing funds past 24 months excess returns on the Fama-French-Carhart four factors. STDDEV is the standard deviation of residuals from regressing funds past 24 months excess returns on the Fama-French-Carhart four factors. Panel A reports the regression results for the full sample. Panel B reports the regression results for the bootstrap sample.

Panel A: Full sample

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Intercept	-0.0008***	-0.0007***	0.0009*	0.0035	0.0039	0.0044	0.0052
	(-3.37)	(-3.18)	(1.81)	(1.18)	(1.29)	(1.34)	(1.54)
Past α	0.3193***	0.2648***	0.2672***	0.2834***	0.2827***	0.2824***	0.2820***
	(7.59)	(5.21)	(5.30)	(6.52)	(6.50)	(6.56)	(6.52)
Turnover	0.0000	-0.0001	0.0000	0.0002	-0.0003	-0.0004	-0.0017
	(0.05)	(-0.46)	(0.10)	(0.96)	(-0.42)	(-0.45)	(-1.10)
Turnover * Past α		0.0497**	0.0462**	0.0511***	0.0503**	0.0506**	0.0494**
		(2.56)	(2.40)	(2.62)	(2.57)	(2.50)	(2.41)
Log(TNA)			-0.0002***	-0.0001**	-0.0001**	-0.0001**	-0.0002**
			(-2.81)	(-2.45)	(-2.49)	(-2.53)	(-2.58)
Fee			-0.0806***	-0.0756***	-0.0770***	-0.0771***	-0.0779***
			(-3.44)	(-3.64)	(-3.67)	(-3.74)	(-3.74)
STDDEV				-0.1007**	-0.1015**	-0.1016**	-0.1020**
				(-2.51)	(-2.54)	(-2.50)	(-2.51)
ActiveShare				0.0017	0.0014	0.0018	0.0012
				(1.53)	(1.10)	(1.56)	(0.92)
Turnover * ActiveShare					0.0005		0.0009
					(0.63)		(1.08)
R2				-0.0032	-0.0032	-0.0041	-0.0044
				(-1.27)	(-1.27)	(-1.44)	(-1.52)
Turnover * R2						0.0007	0.0012
						(0.66)	(0.98)
R-square	5.75	6.40	7.47	14.12	14.42	14.65	14.97

Panel B: Bootstrap sample

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Intercept	-0.0007***	-0.0006***	0.0012**	0.0037	0.0040	0.0050	0.0058*
	(-3.06)	(-2.92)	(2.48)	(1.25)	(1.35)	(1.53)	(1.74)
Past α	0.3192***	0.2723***	0.2775***	0.2847***	0.2859***	0.2822***	0.2831***
	(7.39)	(5.27)	(5.42)	(6.52)	(6.52)	(6.52)	(6.50)
Turnover	0.0000	0.0000	0.0000	0.0002	-0.0002	-0.0008	-0.0021
	(0.19)	(-0.28)	(0.20)	(1.00)	(-0.23)	(-0.78)	(-1.34)
Turnover * Past α		0.0446**	0.0418**	0.0485**	0.0452**	0.0483**	0.0454**
		(2.26)	(2.14)	(2.42)	(2.24)	(2.32)	(2.15)
Log(TNA)			-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
			(-3.69)	(-3.03)	(-3.09)	(-3.12)	(-3.15)
Fee			-0.0814***	-0.0792***	-0.0808***	-0.0809***	-0.0813***
			(-3.30)	(-3.78)	(-3.83)	(-3.91)	(-3.89)
STDDEV				-0.0995**	-0.0998**	-0.1004**	-0.1010**
				(-2.51)	(-2.53)	(-2.49)	(-2.50)
ActiveShare				0.0019*	0.0015	0.0019*	0.0012
				(1.66)	(1.22)	(1.68)	(0.95)
Turnover * ActiveShare					0.0004		0.0010
					(0.47)		(1.15)
R2				-0.0032	-0.0031	-0.0045	-0.0048*
				(-1.27)	(-1.26)	(-1.59)	(-1.67)
Turnover * R2						0.0011	0.0016
						(0.99)	(1.27)
R-square	5.94	6.59	7.70	14.02	14.32	14.55	14.86

Table 3.7: Fixed-Effect Panel Multivariate Regression

This table reports fixed-effect panel multivariate regression results controlling for both fund fixed effect and time (month) effect. The standard errors in Column [1], [2], and [3] are clustered by fund category and month. Fund category is defined by fund size (small vs. large) and fund style (growth vs. value). The standard errors in Column [4], [5], and [6] are clustered by individual fund and month. Past α is the intercept of regressing past 24 month excess returns on Fama-French-Carhart four factors. Log(TNA) is the natural log of total net asset aggregated at the fund level. Fee is the value-weighted expense ratio reported by fund share classes in the nearest fiscal year end. Activeshare is calculated per Cremers and Petajisto (2009). R2 is the R square from regressing funds past 24 months excess returns on the Fama-French-Carhart four factors. STDDEV is the standard deviation of residuals from regressing funds past 24 months excess returns on the Fama-French-Carhart four factors.

	Clustered by category and month			Clustered by fund and month		
	[1]	[2]	[3]	[4]	[5]	[6]
Past α	0.249365***	0.222789***	0.212433***	0.249365***	0.222789***	0.212433***
	(11.98)	(10.02)	(9.98)	(3.69)	(3.32)	(3.19)
Turnover	0.00028***	0.00013***	0.00015***	0.00028	0.00013	0.00015
	(6.90)	(3.40)	(3.68)	(0.09)	(0.04)	(0.06)
Turnover * Past α	0.024328**	0.022709**	0.025971**	0.024328	0.022709	0.025971
	(2.36)	(2.12)	(2.48)	(0.97)	(0.95)	(1.02)
Log(TNA)		-0.000115***	-0.000109***		-0.000115**	-0.000109*
		(-4.86)	(-4.40)		(-2.41)	(-1.84)
Fee		0.000012	0.000024**		0.000012	0.000024**
		(0.74)	(2.32)		(0.65)	(2.08)
R2			-0.002143***			-0.002143
			(-3.96)			(-0.87)
ActiveShare			0.002561			0.002561*
			(1.31)			(1.79)
STDDEV			-0.053426***			-0.053426
			(-3.93)			(-0.75)

Table 3.8: Simulated Fixed-Effect Panel Multivariate Regression

This table reports the results for the simulated fixed-effect panel multivariate regression. In each simulation, for each fund month, we draw with replacement a residual from the regression equation (7) and simulate a dependent variable $\alpha_{i,t+1}$. We then rerun the fixed-effect panel multivariate regression for each simulated sample. The simulation is repeated 2000 times. The Coefficient and t stat are from the regression equation (7). From the simulations, we report the percentage of coefficient and t stat less than 0 in our alternative hypothesis that coefficient doesn't equal to 0. In another set of simulations, we report the percentage of coefficient and t stat less than estimated coefficient and t stat in our null hypothesis that coefficient equals to 0.

	Past α	Turnover	Turnover * Past α
Coefficient	0.212433	0.00015	0.025971
% coefficients less than 0 (alternative)	0	0.0952	0.1324
% coefficients less than estimated coefficient (null)			0.5486
t stat	7.25	2.55	2.03
% t stat less than 0 (alternative)	0	0.0952	0.1324
% t stat less than estimated t stat (null)			0.5848

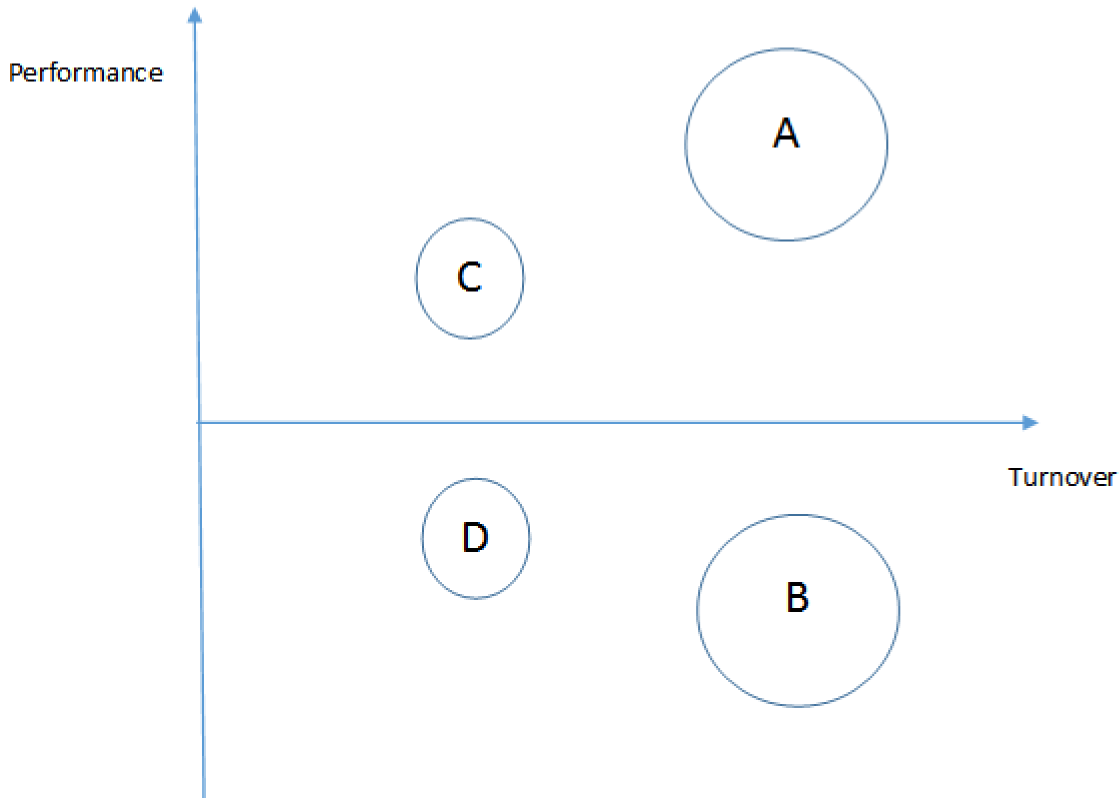

Figure 3. 1: Heterogeneity in the Effect of Turnover on Performance

This figure illustrates the heterogeneity in the effect of turnover on performance between high-turnover funds and low-turnover funds. The size of the circle represents level of turnover. A and B are high-turnover funds. C and D are low-turnover funds.

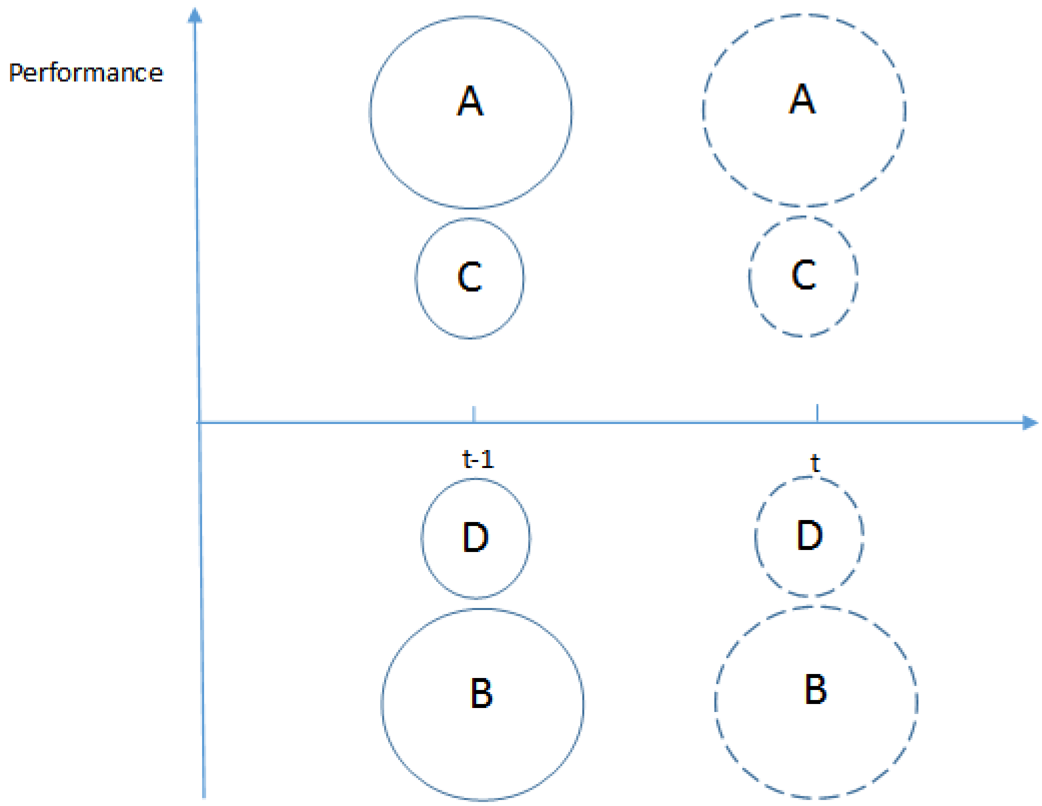

Figure 3. 2: Heterogeneity in the Effect of Turnover on Performance Persistence

This figure illustrates the heterogeneity in the effect of turnover on performance persistence between high-turnover funds and low-turnover funds. The size of the circle represents level of turnover. A and B are high-turnover funds. C and D are low-turnover funds. The horizontal axis represents a time line. The solid-lined circle represents funds at time t-1. The dashed circle represents funds at time t.

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