# Costly Information Production, Information Intensity, and Mutual Fund Performance

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## Abstract

This study 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.



**Keywords**: Mutual fund performance; costly information production; information intensity

# 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 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

[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.

[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.

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? 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

[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.

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 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

[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.

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 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

[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).

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 2 introduces the measure of information intensity at both the stock level and at the fund level. Section 3 describes data.

Section 4 presents the empirical results. Section 5 concludes.

# 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 $\mu_t$ is the instantaneous drift, $\sigma_t$ 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 $\kappa_\tau$ 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 $\kappa_j$ 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 Podolskij (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.

[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.

After obtaining estimates of information intensity $\text{SII}_{it}$ 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-measured fund information intensity:

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

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

# 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

[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.

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 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.

# 4 Empirical Results

## 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 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 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 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.

[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.

Panel B of Table 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 – marketcap, 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 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 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 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.

## 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.

### 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 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.

#### 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 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.

#### 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 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 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.

#### 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 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 5.

Panels A of Table 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 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 5 (0.448%). The funds ranked in the top past-alpha quintile and top II quintile have an alpha of 0.201%, also comparable to the corresponding number reported in Table 5

[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.

(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 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 3. These findings highlight the practical usefulness of the fund information intensity measure to fund investors when they make fund selection decisions.

### 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 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 5 for each of the subperiod.

[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.

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.

## 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 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 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 intensity on fund performance while controlling for various competing effects.

### 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 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 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 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 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 9 by and large confirms their results. Here, funds are independently double-sorted by past alpha and R2. As noted in Section 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 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 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.

#### 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 interwined 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 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 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]

#### 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:

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

[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.

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 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 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 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 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 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 information intensity in predicting fund performance among high past alpha funds is not explained away

[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 8) but significantly predicts the benchmark-adjusted fund performance (their Table 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.

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.

## 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

[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.

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 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 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 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.

### 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 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 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 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

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

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 insignificant.

# 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.

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## Table 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 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 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 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 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 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 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 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 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) |

## Table 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 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 $\alpha1$ to past $\alpha5$) 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 $\alpha$ | 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 $\alpha$ | 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 $\alpha$ | | -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 $\alpha$ | | | 0.0036 | | 0.0032 | 0.0038 |
| | | | (0.43) | | (0.38) | (0.43) |
| ActiveShare | | | | 0.0061 | | -0.0026 |
| | | | | (0.38) | | (-0.23) |
| ActiveShare * Past $\alpha$ | | | | 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 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 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 $\alpha$ | 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 $\alpha$ | 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 $\alpha$ | | 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 $\alpha$ | | | 0.0464 | | 0.0538 | 0.0507 |
| | | | (0.61) | | (0.68) | (0.59) |
| ActiveShare | | | | 0.0683 | | -0.1917* |
| | | | | (0.72) | | (-1.78) |
| ActiveShare * Past $\alpha$ | | | | -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 |