Costly Information Production, Information Intensity, and Mutual Fund Performance

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Abstract

This study examines the concentration of active mutual fund managers' stock selection efforts toward information-intense stocks and the degree to which they are successful in such efforts. Information intensity of a stock is measured by the contribution of jumps to stock return variance. We find that both skilled and unskilled fund managers are attracted to stocks with high information intensity. Moreover, the well-known phenomenon of performance persistence is only observed among funds aggressively investing in high information-intensity stocks. The effect of fund information intensity on fund performance is robust to the control of the return volatility, return skewness, and illiquidity of fund holdings as well as 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 decision by fund managers and an important dimension of fund selection decision 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, "channel-checking" has become a popular type of investment research – 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 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 costly information production by mutual funds – 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 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 experience significant corporate events and deliver large surprises to investors. Such corporate events include, for example, earnings announcements, mergers and acquisitions, product launches or failures, and executive turnovers. Intuitively, if certain information causes a large investor surprise, it should be valuable to obtain beforehand. Note that this notion of information intensity is different from the concept of mispricing, which is defined relative to public information.

[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.

To measure large information surprises and information intensity, we draw on the literature of non-parametrically 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.[5] 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 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

[5] 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.

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 contrast the effect of fund information intensity with the effects of three competing fund holding characteristics, namely, return volatility, return skewness, and illiquidity. Both return volatility and return skewness of fund holdings are negatively related to subsequent fund performance. However, these two characteristics of fund holdings significantly affect the performance of funds with poor past alphas, but insignificantly so on fund with high past alphas. By contrast, information intensity significantly affects the performance of funds with high past alphas, but not so on funds with poor past alphas.[6] Further, we show that the effect of information intensity on fund performance is not subsumed by fund holdings of illiquid stocks. This provides support to the notion that information intensity as a measure of potential reward to private information production is different from trading

[6]The negative relation between volatility of fund holdings and fund performance is consistent with the recent findings of Jordan and Riley (2015), who report that funds with higher return volatility tend to have worse performance. The contrast in our findings suggests that the relation of fund performance with the return volatility and skewness of fund stock holdings is not driven by fund decisions to produce costly information, but rather has a different underpinning – possibly, the preference for lottery-like stocks. Return volatility and return skewness are positively correlated across stocks. Stocks with high volatility and high skewness may may attract managers with lottery preferences, and 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).

frictions that are indicative of mispricing relative to public information.

Third, we compare the information intensity effect with that of fund activeness. Several existing studies have examined the activeness of fund investment strategies 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, 2016). While active funds may engage in strategies that exhibit both large departure from benchmarks and high information intensity in their stock holdings, we find that the relation of information intensity with fund performance is different from that of two activeness proxies in the existing literature – ActiveShare and fund return R2. After controlling for these activeness measures, 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.

Fourth, 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 alphas but low IIs, or relative to funds with high IIs but low past alphas. 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 fund flows are more sensitive to past performance among funds with higher IIs. This result is robust to the control of various fund characteristics, including the volatility, skewness, and illiquidity characteristics of fund holdings, and fund activeness. Thus, investors' fund selection decisions appear to be affected by how fund managers allocate their costly information production efforts and the impact of such effort 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 ones. In this study, we use the non-parametric approach developed in the recent literature (e.g., Barndorff-Nielsen and Shephard, 2004 and 2006) to estimate the contribution of jumps to overall stock return variance. The idea behind this approach is that a quantity known as bi-power variation represents the contribution by the continuous diffusion component of stock price movement to the stock return variance, while the remaining variance can then be attributed to the jump component. Specifically, consider a general, continuous-time, jump-diffusion process for stock price:

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

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

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

And the *bi-power variation* is defined as

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

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 $\to \infty$, 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,

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

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

where K is the total number of jumps during the period and κ_j is the size of the j-th jump. Now define the jump variance as JV=Max(0, RV-BPV).[7] 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).[8]

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.

[7] 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.

[8] 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 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.[9]

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 CRSP database reports fund net returns, flows, investment objectives and other fund characteristics. The Thomson-Reuters database provides quarterly snapshots of mutual fund portfolio holdings. 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

[9] 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.

fund in the CRSP database into a single portfolio (value-weighted, based on beginning-of-quarter total net assets of each share class) before matching the CRSP data with the Thomson-Reuters data. We restrict the sample to U.S. actively managed diversified equity funds that mainly invest in domestic stocks, and 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). Note that there is an increasing trend of II over time. More specifically, 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 averages of JV, RV, return standard deviation and return skewness of stocks held by funds (both standard deviation and skewness measured using daily stock returns during the past 12 months). The weights used to calculate these characteristics are the portfolio weights. Similar to II, we take the rolling four-quarter averages of these measures. The average information intensity of 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, return standard deviation and return skewness 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 stocks with positive skewness; 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).[10] 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 B of Table 2 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

[10]We thank Martijn Cremers for providing the ActiveShare data. R2 is the R-square of regressing monthly fund returns during the past 24 months onto the Carhart (1997) four factors.

quintile, and drops slightly 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.

Panel B of Table 2 further 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 – log 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. Market cap is measured at the end of a quarter. Book-to-market ratio is based on the market value at the end of a quarter and book value for the most recently reported fiscal quarter. To alleviate the influence of the outliers we winsorize the book-to-market ratio at the top and bottom 1% across stocks in each quarter. The Amihud illiquidity ratio is measured using daily data during a calendar quarter. We then use the portfolio weights of a fund to take the weighted average of the standardized stock characteristics across the stocks held by the fund; further, similar to II, we take the rolling four-quarter averages of these style measures. The results show that funds with higher II ranks hold smaller stocks and more illiquid stocks, and have a slight tilt toward holding more growth (low-BM) stocks. The relation of II with the momentum style appears 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 Fund 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.[11] 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

[11] 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.

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 (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.[12] 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. 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 return volatility, return skewness, and illiquidity of fund holdings, as well as the effect of fund activeness measured by ActiveShare and fund return R-square (R2). In Section 4.3.2, we use multivariate regressions to examine the effect of information intensity on fund performance while controlling for various competing effects of fund holding characteristics and fund activeness.

[12] 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 banned, while others –e.g., channel-checking – remain legitimate or in a grey area.

4.3.1 Alternative Effects: Fund Holding Characteristics and Fund Activeness

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 rolling four-quarter average of the weighted average return standard deviation of stocks held by the fund. 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 four-factor alphas of the 25 fund portfolios during the subsequent month. The results show that STDEV 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 is mainly on the performance of funds with low past alphas. For example, among funds with the bottom past alpha rank, those in the top STDEV quintile generate a significantly negative four-factor alpha of -0.390%. They significantly underperform those in the bottom STDEV quintile, which have an insignificantly negative alpha of -0.072%. Meanwhile, among funds in the top past-alpha quintile, the relation between STDEV and performance is basically flat – those in the top STDEV quintile generate a four-factor alpha of 0.062%, indifferent from the alpha generated by those in the bottom STDEV quintile (0.016%).[13]

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.

In addition, we consider the return skewness of fund stock holdings. Since at individual stock level, positive jumps are more frequent than negative jumps (Jiang and Yao 2013), the stock-level information intensity measure SII is likely positively related to stock return skewness. The results reported in Table 2 show that this relation holds at fund level as well, between II and SKEW. This gives rise to the question of whether the return skewness of fund holdings has an impact on fund performance similar to that of II.

To address this question, in Panel B of Table 9 we report the next-month performance (four-factor alpha) of funds double sorted by past alpha and SKEW. We find performance persistence in each SKEW quintile – funds in the top past-alpha quintile significantly outperform funds in the bottom past-alpha quintile regardless of their SKEW quintiles. Thus, SKEW does not have a significant impact on performance persistence. Further, the effect

[13] In a small number of months, a few fund groups (e.g., funds in the bottom quintile of past alpha and bottom quintile of II) do not have any fund observations. As a result, the High-Low differences reported in the last row and last column of the panel are not always equal to differences between the High and Low values reported separately in the panel. We have alternatively produced a set of results by removing a month if any of the 5x5 portfolios is missing for that month. This variation (untabulated) does not substantially change any of the inference here. The same holds for Panels B to E of the table.

of SKEW on fund performance is most visible among the bottom past-alpha funds. There, low-SKEW funds significantly outperform high-SKEW funds. By contrast, for funds in the top past-alpha quintile, SKEW does not significantly affects fund performance. This pattern is likely related to the lottery preference of certain fund managers. It has been well documented that due to lottery preference of certain investors, stocks with large positive skewness tend to be over-valued and have low future returns. Chasing such stocks tend to result in poor performance. This may be particularly relevant for fund managers with poor past performance (an indication of lack of skills).

Further, in Panel C of the table, we report the performance of funds double sorted by past alpha and ILLIQSCORE, a measure of illiquidity of fund holdings. Illiquidity is a form of market fraction that is associated with potential misvaluation relative to public information. Although we argue that information intensity is conceptually different from misvaluation of stocks relative to public information, II may have an intricate empirical relation with trading frictions. This is because for illiquid stocks, information may impound slowly into stock prices, causing large jumps. However, large surprises to investors could take place for reasons unrelated to illiquidity. For example, to avoid competition, firms may provide little voluntary disclosure but instead release a large amount of information at the time of mandatory disclosure (e.g., earnings announcements).

The results in this panel show that illiquidity of fund holdings has a large impact on fund performance. Similar to the effect of II, performance persistence is stronger among funds with higher ILLIQSCOREs. However, unlike the effect of II, ILLIQSCORE affects the performance of funds both with good and poor past performance, and the direction of the impact depends on past alpha. Illiquidity has a significantly negative impact on performance for funds in the bottom past-alpha quintile, and has a significantly positive impact on performance for funds in the top past-alpha quintile.

Next, we turn to a fund activeness measure – R2. Amihud and Goyenko (2013) report that R2 has a significantly negative relation with subsequent fund performance, and that its effect is particularly strong among funds with high past alphas. Panel D of Table 9 by and large confirms their results. Here, funds are independently double-sorted by past alpha and R2. The results 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 performance of funds in the bottom past-alpha quintile, but significantly affects performance of 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 II in Table 5.[14]

In Panel E of the paper, we report the performance of funds double sorted on past alpha and another measure of fund activeness: ActiveShare. We find that the effect of ActiveShare on fund performance is somewhat similar, albeit at a weaker magnitude, to that of R2. Among funds in the top past alpha quintile, those with higher ActiveShare have better performance, although the alpha of funds in the top-II and top past-alpha group is not significant. Further, performance persistence tends to be stronger among funds with higher ActiveShare, although the relation is somewhat non-monotonic.

4.3.2 Controlling for Competing Effects: Multivariate Regressions

Given the significant performance effects by many fund characteristics reported in Table 9, it is important to control for these effects when we evaluate the impact of information intensity. To do so, we perform two sets of Fama-MacBeth multivariate regressions.[15] The regressions are performed each month t across sample funds. The dependent variable in both sets of regressions 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

[14]The results for R2 reported in Panel D here are somewhat weaker relative to those reported by Amihud and Goyenko (2013). In untabulated analysis, we find stronger results for the sample period studied by Amihud and Goyenko (2013), 1990-2010.

[15]We have also used a triple-sorting procedure to control for competing fund characteristics effects, The results show that such controls do not explain away the effect of fund information intensity on fund performance. For brevity we do not tabulate the results of this analysis.

abnormal return $\hat{\alpha}_{j,t}$ is estimated as:

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

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

In the first set of regressions, the main explanatory variables include past fund alpha, II, and their interaction term. Past alpha is estimated from the Carhart four factor model using rolling 12 months of returns, i.e., from month t-12 to month t-1. The key control variables include the five competing fund characteristics, and their interaction terms with past alpha. The competing fund characteristics include STDEV, SKEW, ILLIQSCORE, ActiveShare, and the logit-transformation of R2 (denoted as TR2) following Amihud and Goyenko (2013) (with R2 censored at top and bottom 1%). These fund characteristics and their interaction terms with past alpha are included either separately and jointly in various regression specifications. In this set of regressions, the coefficients on the interaction terms between II and past alpha would tell us whether the relation between past and future performance, i.e., performance persistence, is stronger among funds with higher information intensity, after controlling for the effect of competing fund characteristics.

The results from double-sorting analysis reported in Table 9 show that several competing fund characteristics affect fund performance differently across funds with different past alphas. For example, STDEV and SKEW both have significant impact on fund performance among funds with poor past alphas, while having no effect on performance among funds with strong past performance. Further, the impact of ILLIQSCORE on performance is negative among low past-alpha funds and positive among high past-alpha funds. The first set of regressions described above are not able to capture such differential effects on performance. The second set of regressions are designed to capture such effects. We create five dummies for funds belonging to each of the five quintiles of past alpha. The main explanatory variables include the past-alpha quintile dummies, II, and their interaction terms. The key control variables include one of the competing fund characteristics (STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2), and its interaction term with the past alpha dummies. In this second set of regressions, the coefficients on the interaction terms between II and past alpha quintile dummies would tell us whether information intensity affects fund performance among funds with high past alphas more than its effect on performance of low past alpha funds, after controlling for competing fund characteristics.

In both sets of regressions, to facilitate inference, the variables involved in interaction terms (other than the dummy variables), including II, past alpha, STDEV, SKEW, ActiveShare, and TR2, are cross-sectionally standardized, by first subtracting their cross-sectional means and then divided by their cross-sectional standard deviations. The regressions involving ActiveShare are for the period of 1981-2012 due to data availability. Further, in both sets of regressions, we also include the following additional control variables: log fund size (Log(TNA)), expense ratio (FEE), log fund age (Log(Age)), annual turnover (Turnover), and percentage fund flow during the past quarter (Lagged Flow).[16]

The results for the first set of regressions are reported in Panel A of Table 10. The first regression, reported in Column (1), does not control for the competing effects. The coefficient for past alpha, 0.097 (t=5.65), is significantly positive, confirming the existence of performance persistence.[17] More importantly, the interaction term between past alpha and II is also significantly positive, at 0.0228 (t=2.88). This interaction term continues to have significantly positive coefficients in Column (2) to (7), where the competing fund

[16]In untabulated analysis, we have also included a variable, the earnings announcement window return (EAR) during the II measurement quarter. EAR is the weight average returns of stocks held by the fund during a five-day window, from two days before the announcement date to two days after, with the weights being the portfolio weights at the beginning of the quarter. We include this variable as a control for the effect of post-earnings announcement drift for stocks held by a fund. The results are robust to the inclusion of this control variable.

[17]Generally, with an interaction term, the full effect of past alpha is captured by $\beta_1 + \beta_2 * \overline{\text{II}}$, where β_1 is the coefficient on past alpha, β_2 is the coefficient for the interaction term between past alpha and II, and $\overline{\text{II}}$ is the cross-sectional average of II. But since II is cross-sectionally standardized, $\overline{\text{II}}$ is zero. Thus β_1 represents the full effect of past alpha on future performance.

characteristics are added as controls either separately or jointly. This suggests a robust effect that performance persistence is stronger among funds with higher information intensity.

Among the interaction terms involving competing fund characteristics, that for STDEV has a significantly negative coefficient(Column(2)), and that for ActiveShare has a significantly positive coefficient (Column (6)), although both become insignificant in the joint regression reported in Column (7). The coefficients for the interaction terms involving SKEW, ILLIQSCORE, and TR2 are insignificant. The coefficient for STDEV has a significantly negative coefficient, consistent with the finding of Jordan and Riley (2015). In addition, fund size and expense ratio have significantly negative impact on fund performance, while the effects of fund age, turnover, and lagged flow are insignificant.

Now turn to Panel B of the table, which reports the results for the second set of regressions. In Column (1), the coefficients for the key variable of interest, the interaction term between II and past alpha dummies, increase from -0.0343 (t=-1.80) to 0.0607 (t=3.18) as we move from the bottom to the top past-alpha quintile. As reported toward the bottom of the table, the difference in the coefficients of the interaction terms between the top and bottom past-alpha quintiles is 0.0949 (t=4.57). This suggests that the impact of II on fund performance is significantly higher for funds in the top past-alpha quintile than for funds in the bottom quintile. Regressions reported in Columns (2) to (6) control for the effects of STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2 respectively. Across these regressions, the coefficient for the interaction between II and the top past-alpha dummy is always significantly positive, and so is the difference in the interaction of II and past alpha dummies between the top and bottom past-alpha quintiles. That is, controlling for competing effects does not explain away the fact that impact of II on fund performance is higher among funds with higher past alphas.

The coefficients on the interaction terms of the bottom past-alpha dummy with both STDEV and SKEW are significantly negative, while their interaction terms with the top past-alpha dummy are insignificant, suggesting that return volatility and return skewness of fund holdings mainly affect the performance of poorly performing funds. This is consistent with the results based on double sorting reported in Table 9. The coefficient on the interaction term involving ILLIQSCORE is significantly positive for the top past-alpha quintile, consistent with the results from double-sorting reported in Table 9. However the coefficient is insignificant for its interaction term with the bottom past-alpha quintile dummy. Interestingly, the interaction term involving ActiveShare is significantly negative for the bottom past-alpha quintile, while insignificant for the top past-alpha quintile. This is different from the double-sorting results in Table 9. Finally, there are no significant coefficients for interaction terms involving TR2; its effect is likely subsumed by other variables in the multivariate regression setting.

Overall, the results in Table 10 confirm that the effect of II on fund performance are robust to the control of various competing effects.

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.[18] Unfortunately, tracking all the wide varieties of events is impossible. Instead, we focus on two types of corporate events – earnings announcements and M&A announcements. To gauge the impact of the events to stock returns, we compute the event window return as the cumulative stock return during the five-day window, from two days before the announcement date to two days after. We then compute the quarterly fund-level event-window performance as the weighted average event-window returns during a quarter for stocks held by the fund, using the beginning-of-quarter portfolio weights. Given the association between these two types of events and stock price jumps, the event-window performance at least in part reflects the effectiveness of funds in

[18] 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.

turning rewarding information production opportunities into actual information production.

Table 11 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 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 Flow Sensitivity to Past Performance

Given the significant impact of information intensity on fund performance, we ask whether fund investors are aware of this effect when allocating their fund investments. 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 regression is the percentage fund flow during the quarter after measuring II. The main explanatory variables include the past four-factor alpha (estimated using past 12 months of data), II, and their interaction term. The control variables include the five fund characteristics examined in Table 10– STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2, and their interaction terms with past alpha. These fund characteristics are included separately and jointly in regressions. In addition, we include log fund TNA, expense ratio, log fund age, annual turnover, and percentage fund flow during the past quarter.[19] To facilitate inference, all variables involved in the interaction terms – past alpha, II, STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2 – are cross-sectionally standardized. We perform cross-sectional regressions each quarter, and then average the coefficients over time. The impact of II on the flow-performance sensitivity is captured by the coefficient on the interaction term between past alpha and II.

The results are reported in Table 12. Column (1) reports the results for the regression that does not include any of the five controlling fund characteristics. For this regression, past alpha has a significantly positive coefficient of 1.6857, indicating that fund flows do chase performance. More importantly, the interaction term of II and past alpha is significantly positive, at 0.1596, suggesting that flows are more sensitive to performance for funds with higher IIs. The coefficients for past alpha and for its interaction with II both remain significantly positive in the regression results of Column (2) to (7), where we separately and jointly control for the five competing fund characteristics and their interaction terms with

[19] In untabulated analysis, we have also performed regressions with the same set of explanatory variables as the second set of performance regressions reported in Panel B of Table 10. The effect of information intensity on the flow-performance sensitivity is robust to this variation of regression specification.

past alpha.

The interaction term between past alpha and STDEV is significantly negative (Column (2)), suggesting that holding volatile stocks in a fund portfolio reduces flow sensitivity to past performance. The interaction terms of past alpha with the other four fund characteristics – SKEW, ILLIQSCORE, ActiveShare, and TR2, are insignificant. However, the coefficient for ILLIQSCORE is significantly positive (Column (4)), and the coefficient for TR2 is significantly negative (Column (5)), suggesting that investors are in general attracted to funds holding illiquid stocks and funds with distinctive returns from benchmarks, regardless of their past performance (although the coefficient for TR2 becomes insignificant in joint regressions). In addition, in the joint regression (Column (7)), the coefficient for SKEW is significantly positive, possibly suggesting a lottery like preference by fund investors when they pick funds. Finally, consistent with patterns reported in the existing literature, the table shows that fund size and age are negatively correlated with subsequent fund flows, while turnover and past flow are positively correlated with subsequent flows.

Overall, 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.

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), return skewness (SKEW), and two measures of fund activeness, ActiveShare and R2. Panel B reports the following fund characteristics: the number of stock holdings, annual fund turnover, 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

II Rank	II (%)	JV (%)	RV (%)	STDEV (%)	SKEW	ActiveShare	R2
1-Low	6.87	0.43	5.23	1.96	0.12	0.77	0.90
2	7.93	0.53	5.35	2.01	0.13	0.78	0.91
3	8.74	0.66	5.93	2.13	0.15	0.83	0.90
4	9.78	0.92	7.21	2.34	0.18	0.89	0.89
5-High	11.77	1.37	8.85	2.59	0.21	0.94	0.88
High-Low	4.90	0.94	3.62	0.63	0.09	0.17	-0.02
t stat	(22.52)	(9.19)	(8.02)	(3.17)	(9.18)	(13.27)	(-2.81)

Panel B

II Rank	Holdings #	Turnover (%)	TNA ($m)	Fee (%)	Age (Yrs)	SIZE-SCORE	BM-SORE	MOM-SCORE	ILLIQ-SCORE
1-Low	75	77	1,417	1.11	19.9	2.22	-0.07	0.18	-0.13
2	98	80	1,323	1.11	18.9	2.11	-0.07	0.16	-0.13
3	102	84	1,056	1.17	17.0	1.87	-0.08	0.18	-0.12
4	102	90	778	1.24	14.9	1.51	-0.10	0.21	-0.12
5-High	99	89	526	1.32	12.5	1.04	-0.11	0.23	-0.13
High-Low	25	13	-892	0.21	-7.4	-1.18	-0.04	0.05	0.01
t stat	(9.44)	(3.35)	(-4.97)	(13.18)	(-6.19)	(-15.32)	(-2.79)	(1.67)	(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 25 (5x5) fund portfolios formed on monthly independent double-sorts by past alpha and information intensity II. Past alpha is estimated from the Carhart four-factor model using rolling 12-month after-expense fund returns. The performance measures include after-expense net return in Panel A, after-expense four-factor alpha in Panel B, and Characteristic Selectivity in 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 25 (5x5) fund portfolios double-sorted by past alpha and lagged fund information intensity measure II. Past alpha is estimated from the Carhart four-factor model using past 12 months of after-expense fund returns. In Panels A to D, the information intensity measure II is lagged by one to four quarters respectively. The reported performance is the 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 performance of funds double-sorted by past alpha and information intensity II in two subperiods: 1980-1996 in Panel A and 1997-2014 in Panel B. Past alpha is estimated from the Carhart four-factor model using past 12 months of after-expense fund returns. The reported performance is the after-expense four-factor alpha, in percentage points.

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. In Panel A to E, funds are double sorted by past alpha and one of the following five characteristics – return volatility of fund holdings (STDEV), return skewness of fund holdings (SKEW), illiquidity of fund holdings (ILLIQSCORE), the regression R-square (R2) of the Carhart four-factor model, and ActiveShare. Past alpha is estimated using past 12 months of after-expense returns under the Carhart four-factor model. The reported performance measure is the after-expense four-factor alpha, in percentage points.

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 SKEW

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

Panel C: Funds double-sorted by past alpha and ILLIQSCORE

	ILLIQSCORE					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.101*	-0.107**	-0.162***	-0.285***	-0.327***	-0.234***
	(-1.84)	(-2.08)	(-3.27)	(-4.98)	(-4.97)	(-3.42)
2	-0.097***	-0.071**	-0.099**	-0.123***	-0.190***	-0.093*
	(-3.12)	(-2.05)	(-2.30)	(-2.83)	(-3.45)	(-1.77)
3	-0.057**	-0.103***	-0.076**	-0.099**	-0.057	0.000
	(-1.99)	(-3.32)	(-2.17)	(-2.33)	(-1.08)	(0.00)
4	-0.090***	-0.090***	-0.047	-0.044	-0.004	0.086*
	(-2.98)	(-2.58)	(-1.21)	(-0.94)	(-0.09)	(1.91)
5-High	-0.033	0.059	0.014	0.073	0.140**	0.173***
	(-0.67)	(1.21)	(0.25)	(1.28)	(2.40)	(2.87)
High-Low	0.072	0.165**	0.176***	0.358***	0.467***	0.402***
	(0.97)	(2.47)	(2.60)	(5.11)	(6.04)	(4.80)

Panel D: 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 E: Funds double-sorted by past alpha and ActiveShare

	Activeshare					
Past Alpha	1-Low	2	3	4	5-High	High-Low
1-Low	-0.160***	-0.145***	-0.114**	-0.223***	-0.289***	-0.114
	(-3.95)	(-3.47)	(-2.33)	(-3.61)	(-3.64)	(-1.47)
2	-0.083***	-0.104***	-0.097**	-0.104*	-0.123*	-0.049
	(-3.13)	(-3.02)	(-2.03)	(-1.83)	(-1.81)	(-0.69)
3	-0.088***	-0.106***	-0.074*	-0.046	-0.040	0.045
	(-3.81)	(-3.58)	(-1.83)	(-0.82)	(-0.60)	(0.66)
4	-0.069***	-0.101***	-0.065*	-0.017	-0.058	0.008
	(-2.80)	(-3.33)	(-1.66)	(-0.33)	(-0.95)	(0.12)
5-High	-0.076	0.000	-0.001	0.034	0.082	0.165**
	(-1.59)	(0.00)	(-0.03)	(0.55)	(1.27)	(2.27)
High-Low	0.095	0.141**	0.116	0.264***	0.378***	0.281***
	(1.58)	(2.37)	(1.60)	(3.45)	(4.87)	(3.62)

Table 10: Fama-MacBeth Multivariate Regressions

This table reports results of Fama-MacBeth regressions that analyze the impact of information intensity on fund performance. 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 main control variables include five fund characteristics – STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2 (logit transformation of R2) – and their interactions with past alpha. In Panel B, the main explanatory variables include quintile dummies for past alpha, II, and their interactions. The main control variables include one of the five fund characteristics and their interactions with quintile dummies for past alpha. The control variables in both panels also include log fund TNA, expense ratio, log fund age, fund turnover, and lagged flow. Variables involved in the interaction terms, including past alpha, II, STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2, are cross-sectionally standardized before used in the regressions.

Panel A

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Intercept	0.1629***	0.1285**	0.1391**	0.1617***	0.1592***	0.1767***	0.1280**
	(2.64)	(2.19)	(2.33)	(2.69)	(2.62)	(2.71)	(2.18)
Log(TNA)	-0.0140***	-0.0100**	-0.0133**	-0.0139***	-0.0143***	-0.0144**	-0.0102**
	(-2.60)	(-2.06)	(-2.55)	(-2.61)	(-2.70)	(-2.38)	(-2.00)
Fee	-0.1175***	-0.0964***	-0.1116***	-0.1168***	-0.1192***	-0.1148***	-0.0954***
	(-5.31)	(-5.17)	(-5.33)	(-5.47)	(-5.43)	(-5.24)	(-5.09)
Log(Age)	-0.0076	-0.0120*	-0.0051	-0.0078	-0.0067	-0.0110	-0.0132**
	(-1.09)	(-1.81)	(-0.73)	(-1.13)	(-0.97)	(-1.56)	(-2.04)
Turnover	-0.0002	-0.0001	-0.0002	-0.0002	-0.0002	-0.0002	0.0000
	(-1.35)	(-0.49)	(-1.17)	(-1.32)	(-1.40)	(-1.15)	(0.06)
Lagged Flow	0.0012	0.0002	0.0013	0.0012	0.0008	0.0009	-0.0004
	(0.34)	(0.08)	(0.38)	(0.36)	(0.24)	(0.24)	(-0.13)
Past α	0.0970***	0.0899***	0.1007***	0.0969***	0.0908***	0.0906***	0.0898***
	(5.65)	(5.37)	(5.81)	(5.64)	(5.45)	(5.11)	(5.55)
II	0.0266*	0.0451***	0.0249*	0.0266*	0.0258*	0.0258*	0.0407***
	(1.93)	(3.00)	(1.81)	(1.77)	(1.89)	(1.77)	(2.60)
II * Past α	0.0228***	0.0199**	0.0213***	0.0214**	0.0232***	0.0213**	0.0167*
	(2.88)	(2.20)	(2.61)	(2.55)	(2.99)	(2.18)	(1.92)
STDEV		-0.0446*					-0.0640**
		(-1.67)					(-2.22)
STDEV * Past α		0.0176*					0.0130
		(1.89)					(1.25)
SKEW			-0.0084				0.0051
			(-0.67)				(0.45)
SKEW * Past α			0.0058				-0.0025
			(0.83)				(-0.36)
ILLIQSCORE				0.0038			-0.0050
				(0.38)			(-0.42)
ILLIQSCORE * Past α				0.0049			-0.0049
				(0.49)			(-0.49)
TR2					-0.0024		0.0104
					(-0.21)		(0.92)
TR2 * Past α					-0.0116		0.0049
					(-1.54)		(0.65)
ActiveShare						-0.0006	0.0171
						(-0.04)	(1.20)
ActiveShare * Past α						0.0239**	0.0163
						(2.10)	(1.56)
R-squared	0.09	0.14	0.11	0.10	0.11	0.11	0.18

Panel B

	[1]	[2]	[3]	[4]	[5]	[6]
Competing effect (X)		STDEV	SKEW	ILLIQSCORE	ActiveShare	TR2
Log(TNA)	-0.0130**	-0.0101**	-0.0115**	-0.0151***	-0.0140**	-0.0132**
	(-2.35)	(-2.00)	(-2.11)	(-2.70)	(-2.25)	(-2.46)
Fee	-0.1216***	-0.1013***	-0.1180***	-0.1243***	-0.1161***	-0.1232***
	(-5.49)	(-5.14)	(-5.46)	(-5.68)	(-5.17)	(-5.50)
Log(Age)	-0.0094	-0.0133**	-0.0078	-0.0085	-0.0122*	-0.0082
	(-1.34)	(-2.06)	(-1.12)	(-1.25)	(-1.75)	(-1.19)
Turnover	-0.0002*	-0.0001	-0.0002	-0.0002*	-0.0002	-0.0002
	(-1.73)	(-0.69)	(-1.62)	(-1.71)	(-1.50)	(-1.63)
Lagged Flow	0.0015	0.0004	0.0011	0.0014	0.0009	0.0013
	(0.42)	(0.11)	(0.33)	(0.39)	(0.25)	(0.35)
Past $\alpha 1$	0.0570	0.0508	0.0265	0.0659	0.0759	0.0508
	(0.88)	(0.80)	(0.40)	(1.02)	(1.12)	(0.78)
Past $\alpha 2$	0.1436**	0.1039*	0.1221*	0.1516**	0.1582**	0.1413**
	(2.24)	(1.67)	(1.88)	(2.37)	(2.34)	(2.19)
Past $\alpha 3$	0.1729***	0.1326**	0.1518**	0.1849***	0.1832***	0.1699***
	(2.71)	(2.11)	(2.34)	(2.88)	(2.70)	(2.62)
Past $\alpha 4$	0.2070***	0.1686***	0.1891***	0.2178***	0.2171***	0.2006***
	(3.29)	(2.73)	(2.96)	(3.46)	(3.26)	(3.16)
Past $\alpha 5$	0.2851***	0.2510***	0.2682***	0.2899***	0.2851***	0.2714***
	(4.43)	(3.94)	(4.07)	(4.49)	(4.23)	(4.27)
II * Past $\alpha 1$	-0.0343*	0.0039	-0.0331*	-0.0203	-0.0099	-0.0316
	(-1.80)	(0.87)	(-1.71)	(-1.03)	(-0.48)	(-1.64)
II * Past $\alpha 2$	0.0102	0.0319*	0.0088	0.0073	0.0106	0.0076
	(0.60)	(1.70)	(0.51)	(0.40)	(0.57)	(0.46)
II * Past $\alpha 3$	0.0272*	0.0428**	0.0206	0.0147	0.0212	0.0264*
	(1.71)	(2.45)	(1.26)	(0.82)	(1.21)	(1.68)
II * Past $\alpha 4$	0.0305**	0.0449**	0.0258	0.0229	0.0314*	0.0294*
	(2.03)	(2.55)	(1.60)	(1.36)	(1.85)	(1.93)
II * Past $\alpha 5$	0.0607***	0.0595***	0.0587***	0.0504**	0.0513**	0.0587***
	(3.18)	(2.73)	(2.88)	(2.42)	(2.29)	(3.17)
X * Past $\alpha 1$		-0.1185***	-0.0294*	-0.0260	-0.0580**	0.0251
		(-3.96)	(-1.68)	(-1.63)	(-2.29)	(1.48)
X * Past $\alpha 2$		-0.0496	-0.0065	0.0060	0.0008	-0.0110
		(-1.61)	(-0.41)	(0.47)	(0.05)	(-0.67)
X * Past $\alpha 3$		-0.0415	0.0047	0.0254*	0.0116	-0.0049
		(-1.36)	(0.30)	(1.85)	(0.68)	(-0.31)
X * Past $\alpha 4$		-0.0394	-0.0024	0.0135	0.0053	-0.0013
		(-1.22)	(-0.14)	(1.08)	(0.29)	(-0.08)
X * Past $\alpha 5$		-0.0356	-0.0038	0.0376**	0.0368	-0.0273
		(-1.08)	(-0.20)	(2.29)	(1.34)	(-1.31)
II * Past $\alpha 5$ - II * Past $\alpha 1$	0.0949***	0.0556**	0.0918***	0.0707***	0.0612**	0.0904***
	(4.57)	(2.05)	(4.17)	(3.13)	(2.48)	(4.26)
R-squared	0.15	0.20	0.18	0.17	0.18	0.18

Table 11: 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 12: Impact of Information Intensity on Flow-Performance Relations

This table reports the results of Fama-MacBeth regressions on the effect of information intensity on flow-performance sensitivity. The dependent variable is the quarterly fund flow expressed in percentage points. The main explanatory variables include past alpha, II, and their interaction term. The main control variables include one of the five fund characteristics – STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2 (logit transformation of R2) – and their interaction terms with past alpha, as well as log fund TNA, expense ratio, log fund age, fund turnover, and lagged flow. Variables involved in the interaction terms, including past alpha, II, STDEV, SKEW, ILLIQSCORE, ActiveShare, and TR2, are cross-sectionally standardized.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Intercept	7.4435***	7.6941***	7.4410***	7.4335***	7.5679***	7.6401***	7.8490***
	(11.81)	(11.99)	(11.56)	(11.95)	(12.01)	(11.22)	(11.04)
Log(TNA)	-0.1673***	-0.1774***	-0.1671***	-0.1675***	-0.1611***	-0.1656***	-0.1652***
	(-3.27)	(-3.54)	(-3.21)	(-3.33)	(-3.23)	(-2.96)	(-3.03)
Fee	0.0243	0.0195	-0.0163	0.0153	-0.0557	0.0472	-0.0466
	(0.13)	(0.11)	(-0.09)	(0.08)	(-0.30)	(0.25)	(-0.24)
Log(Age)	-1.2080***	-1.2570***	-1.1991***	-1.1994***	-1.2170***	-1.2379***	-1.2783***
	(-14.05)	(-14.59)	(-14.01)	(-14.37)	(-14.16)	(-13.58)	(-14.09)
Turnover	0.0034**	0.0037***	0.0035**	0.0032**	0.0033**	0.0037**	0.0046***
	(2.32)	(2.64)	(2.42)	(2.21)	(2.28)	(2.44)	(3.08)
Lagged Flow	0.2135***	0.2080***	0.2125***	0.2123***	0.2128***	0.2165***	0.2095***
	(12.20)	(11.90)	(12.02)	(12.08)	(12.14)	(11.63)	(11.23)
Past α	1.6857***	1.8336***	1.6815***	1.6972***	1.7278***	1.7987***	1.8686***
	(14.36)	(14.50)	(14.10)	(14.78)	(15.76)	(14.04)	(14.46)
II	0.1848*	0.1919	0.1758*	0.0148	0.1856*	0.1840*	0 0.0842
	(1.77)	(1.56)	(1.70)	(0.15)	(1.79)	(1.74)	(0.69)
II * Past α	0.1596**	0.2898***	0.1792***	0.1553*	0.1371*	0.1876**	0.3096**
	(2.28)	(3.58)	(2.58)	(1.84)	(1.93)	(2.18)	(2.40)
STDEV		-0.1577					-0.3005*
		(-1.01)					(-1.80)
STDEV * Past α		-0.3476***					-0.3953***
		(-4.24)					(-3.97)
SKEW			0.0924				0.2033**
			(1.10)				(2.50)
SKEW * Past α			0.0669				0.1223
			(0.85)				(1.29)
ILLIQSCORE				0.3342***			0.2523***
				(3.93)			(2.59)
ILLIQSCORE * Past α				0.0447			0.0555
				(0.60)			(0.59)
TR2					-0.2006**		-0.1123
					(-2.53)		(-1.32)
TR2 * Past α					0.0312		0.0673
					(0.44)		(0.88)
ActiveShare						0.0667	0.0061
						(0.71)	(0.08)
ActiveShare * Past α						-0.1045	0.0559
						(-1.09)	(0.55)
R-squared	0.14	0.15	0.15	0.15	0.15	0.15	0.18