An Information Factor: Can Informed Traders Earn Abnormal Profits?*

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First Draft: December 2016
This Draft: November 2018

*We are grateful to Dave Rapach and conference and seminar participants at Baruch College, Beijing University, Emory University, Georgia State University, Indiana University, Rutgers University, Shanghai University of Finance and Economics, St. Louis University, University of China, Washington University in St. Louis, the 2018 Conference on Financial Predictability and Big Data, and the 2018 Northern Finance Association Conference for insightful and helpful comments. All errors are our own.

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Abstract

We construct an *information factor* based on the informed stock buying of firm insiders and the informed selling of short sellers and option traders. The *information factor* strongly predicts future stock returns – a long-short portfolio based the *information factor* earns an average monthly return of 1.33%, substantially outperforming existing strategies including momentum. Moreover, it generates a monthly alpha of 1.29%, suggesting significant compensation for information acquisition and processing. The *information factor* drives hedge fund returns in both the time-series and cross-section. A one standard deviation increase in the *information factor* is associated with a 0.43% increase in the value of aggregate hedge fund portfolios. In the cross-section, funds with high fund information skill (FIS), measured as the covariation between fund returns and the *information factor*, outperform low-FIS funds by 0.32% per month. The results suggest that skill in generating and processing information is an important source of abnormal returns.

Keywords: Hedge Funds, Informed Trading, Insider Trading, Option Trading, Short Selling

JEL Classification Numbers: G11, G12, G14, G17, G23

I. Introduction

Ever since Jegadeesh and Titman (1993), the momentum anomaly has been shown to be one of the most robust and persistent anomalies (Schwert (2003)). It is perhaps surprising that something as simple as past returns can consistently predict the cross section of future stock returns. Yet, empirical research has also documented strong evidence that the *trades* of informed market participants contain information about future returns.[1] An open question is whether a zero-cost strategy like the momentum, but based on informed trades, can do as well or better than using past prices alone.

In this paper, we construct an information factor (hereafter, $INFO$) based on the informed trading of firm insiders, short sellers, and option traders. Specifically, the $INFO$ factor is calculated as the return on a long-short portfolio based on purchases by firm insiders and sales by short sellers and option traders. In contrast to the well-known momentum factor that has a monthly average returns of 0.47%, over our sample period from February 1996 to December 2015 the $INFO$ factor yields a monthly average return of 1.24%, more than twice as much as momentum. Moreover, the standard deviation of the $INFO$ is only 2.65, less than half that of the momentum factor. Our results show that an economic information strategy substantially outperforms a price-based strategy of buying winners and selling losers.

We also find that the $INFO$ factor is a key driver of hedge fund returns. Given that the $INFO$ facor is highly profitable and the information used to construct it is publicly observable, a skilled hedge fund manager is likely to exploit it to enhance her managed portfolio. Indeed, we find that our $INFO$ factor can explain a significant portion of hedge fund returns, both in the time-series and the cross-section. A one standard deviation increase in the $INFO$ factor is associated with a 0.65% increase in the value of the aggregate hedge

[1] See, for example, Lakonishok and Lee (2001); Marin and Olivier (2008); Jagolinzer (2009); Cohen, Malloy, and Pomorski (2012); Desai, Krishnamurthy, and Venkataraman (2006); Boehmer, Jones, and Zhang (2008); Karpoff and Lou (2010); Hirshleifer, Teoh, and Yu (2011); Engelberg, Reed, and Ringgenberg (2012); Pan and Poteshman (2006); Roll, Schwartz, and Subrahmanyam (2010); Johnson and So (2012).

fund portfolios. In the cross-section, high fund information skill (FIS) funds, measured as the covariation between fund returns and the information factor, outperform low-FIS funds by 0.43% per month on a risk-adjusted basis. The results show that hedge funds, which are skilled at exploiting information with respect to firm fundamentals, deliver superior future returns.

Why is the $INFO$ factor informative about future returns? In a sense, the $INFO$ factor is a revealed preference measure of the beliefs of skilled traders. A number of papers find evidence that the *trades* of informed market participants contain information about future returns. First, a stream of literature documents that the trading activity of corporate insiders contains information about manager's beliefs about the prospects of their firms. As a result, it predicts returns in the cross-section (e.g., Lakonishok and Lee (2001); Marin and Olivier (2008); Jagolinzer (2009); Cohen et al. (2012)). In particular, there is strong evidence that insider purchases predict higher future stock returns, and this result is robust to numerous measures of firm-level insider trading (e.g., Lakonishok and Lee (2001); Jeng, Metrick, and Zeckhauser (2003)). However, insider sales are relatively uninformative. For example, Jeng et al. (2003) show that insider purchases earn abnormal returns but insider sales do not. Accordingly, we use net purchases by insiders as a measure of positive private information, which serves as a proxy for the long side of the $INFO$ factor.

Second, a number of papers find direct evidence that short sellers tend to be informed traders (e.g., Desai et al. (2006); Boehmer et al. (2008); Karpoff and Lou (2010); Hirshleifer et al. (2011); Engelberg et al. (2012)). For example, Boehmer et al. (2008) show that non-program institutional short sales contain negative information about future returns. Engelberg et al. (2012) find that short sellers earn large returns by trading soon after the release of public information, suggesting that short sellers are skilled at processing public information signals. Moreover, prior research documents strong evidence that option trading volumes are driven by informed trades (e.g.,Pan and Poteshman (2006); Roll et al. (2010); Johnson and So (2012)). In particular, informed agents may trade options more frequently for negative signals than positive ones due to equity short-sale costs. For example, Johnson and So (2012) show that unsigned total option volume, scaled by the total equity volume, is a strong negative cross-sectional signal of future returns. They find evidence to support the view that traders with negative news are more likely to switch from equities to options when short-sale costs increase. Motivated by this idea, we also use the ratio of option volume to equity volume as a complementary measure of informed trading on the short side. Accordingly, to construct we use we use the sum of short interest and option trading as a measure of negative private information, which serves as a proxy for the short side of the $INFO$ factor.

Our $INFO$ factor is unique in combining the positive signals from insider trades with the negative signals from short selling activities and option trades. This combination captures the economic fundamental information of both good and bad news in the cross-section of stocks. In particular, we first construct an information score for each stock in each month based on the informed trading of firm insiders, short sellers, and option traders. Specifically, for each measure of informed trading, we assign a rank (from 1 to 100) to each stock, where a higher rank is assigned to the value of the informed trading variable associated with a higher level of positive private information. A stock's information score is the arithmetic average of its ranking percentile for each of the three information trading variables. Our $INFO$ factor goes long the decile of stocks with the highest information score and shorts the decile of stocks with the the lowest information score. The $INFO$ factor has a number of desirable attributes. First, it performs significantly better than strategies that use only the long-side or the short-side of trading by informed market participants. Second, it outperforms well-known factors in the existing literature. Over the period from February 1996 through December 2015, the $INFO$ factor's average return of 1.33% per month substantially exceeds the 0.47%, 0.57%, 0.24%, and 0.18% per month of the momentum, the market portfolio, the Fama and French (1993) size factor, and the Fama and French (1993) book-to-market factor. In terms of the Sharpe ratio, the $INFO$ factor has a monthly value of 0.33 (1.14 annualized), more than quintupling that of the momentum factor and quadrupling that of the market portfolio over our sample period. To provide further insights on the profitability of the $INFO$ factor, we compare the cumulative returns for the $INFO$ factor with those of the S&P 500 index. An investment in our $INFO$ strategy yields a cumulative return of 1639% from February 1996 to December 2015, whereas investing in the S&P 500 generates a cumulative return of only 238% over the same period. Moreover, the $INFO$ factor consistently outperforms the S&P 500 index after the year 2000. Its stable performance also suggests that the superior performance of the $INFO$ factor is unlikely to be a result of outliers.

To explore the possibility that our $INFO$ factor could be explained by other risk factors, we examine risk-adjusted returns (alphas) instead of raw returns for the $INFO$ factor. Specifically, we calculate alphas with respect to the Fama and French (1993) three-factor model augmented with Pastor and Stambaugh (2003) liquidity factor (hereafter FF3+LIQ model), Fama and French (2014) five-factor model (hereafter FF5 model), and Hou, Xue, and Zhang (2015) q-factor model (hereafter HXZ model), respectively. The $INFO$ factor, has a monthly "FF3+LIQ" alpha of 1.29%, a "FF5" alpha of 1.26%, and a "HXZ" alpha of 1.31% per month. In contract, the momentum (UMD) factor, has a "FF3+LIQ" alpha of 0.71%, a "FF5" alpha of 0.48%, and a "FF5" alpha of 0.05% per month, which are significantly lower than those of the $INFO$ factor. Mean-variance spanning tests reveal that the $INFO$ factor cannot be replicated by any combination of these well known factors. In addition, Sharpe (1988) style regressions indicate that a considerable proportion of $INFO$'s superior performance can be explained by the return premium of growth stocks and, to a lesser degree, small stocks.[2] Interestingly, these stocks are more likely to be subject to high information asymmetries, thereby rendering a greater advantage to informed traders.[3]

Moreover, we further explore whether the return on the $INFO$ factor captures compen-

[2]Importantly, however, we note that our results are not simply repackaging the well-known premium to growth and small stocks, as evidenced by the $INFO$ factor's large Fama-French alphas and the fact that spanning tests show the $INFO$ factor cannot be replicated by any combination of these well known factors.

[3]For example, a large stock with low growth expectations (i.e., a large capitalization value stock) is less likely to have information asymmetries regarding its fundamental value.

sation for exposure to systematic risk. Following Daniel and Titman (1997), we perform double sorts by first sorting stocks into quintiles based on their characteristics (the level of short interest, the level of option trades, or the level of net insider buy orders) and then sorting into quintiles based on their loadings on the $INFO$ factor. Interestingly, our results show that after controlling for each stock's level of short interest, option trading, and insider trading, there is not a statistically significant relation between each stock's return and its loading on the $INFO$ factor. In other words, the results suggest that the $INFO$ factor is not compensation for systematic risk, but rather, it measures the returns to costly information acquisition and processing.

Given that the data we use to construct the $INFO$ factor is publicly observable, a skilled hedge fund manager should be able to use it to enhance her managed portfolio. Accordingly, we examine whether the performance of hedge funds is attributable to their ability to gather and process private information, which could be due to either following public signals that contain information or having private information.[4] Existing evidence suggests that hedge fund managers are, in general, informed investors. From the long-side perspective, Agarwal, Jiang, Tang, and Yang (2013) find that the confidential holdings of hedge funds have strong return predictability. Cao, Chen, Goetzmann, and Liang (2016) find that undervalued stocks with larger hedge fund ownership realize higher returns. DeVault, Sias, and Starks (2014) show that shocks to hedge fund demand can predict stock returns. From the short-side perspective, Choi, Park, Pearson, and Sandy (2017) show that hedge fund short sales are highly profitable.[5] Accordingly, if hedge fund performance is due, in part, to their ability

[4]A relation between hedge fund trading (and performance) and the $INFO$ strategy could arise for two different reasons: (1) hedge fund managers might condition their trading decisions on the variables we use to construct the $INFO$ factor; or (2) hedge fund managers and other informed traders (insiders, short sellers, and option traders) might condition their trades on the same latent signals about fundamental value, thereby inducing a relation between the variables. Disentangling these two reasons is beyond the scope of the paper.

[5]We note that it is likely that some of the short sales and option trades we observe are due to trading by hedge fund managers. Nonetheless, it is not clear, a priori, that hedge funds that have strategies that following the $INFO$ will necessarily earn higher returns than hedge funds that do not. Put differently, it does not have to be true that hedge funds that co-vary with the $INFO$ factor outperform hedge funds that do not co-vary with the $INFO$ factor. Ultimately, it remains an empirical question whether the $INFO$ factor drives performance by hedge funds.

to generate and process fundamental information, then we would expect a positive relation between the $INFO$ factor and fund performance. We find that this is the case.

We first examine the time-series covariation between hedge fund index returns and the $INFO$ factor. Constructing eight hedge fund indices from the TASS database over the 1996–2015 period, we identify a robust positive relation between the returns to the $INFO$ factor and hedge fund returns. A one standard deviation increase in the loading on the $INFO$ factor is associated with a contemporaneous increase of 0.43% in the value of the aggregate hedge fund index, after controlling for the loadings of hedge fund returns on the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. In other words, the periods of time that hedge funds perform well are the same periods of time that the $INFO$ factor performs well.[6] Furthermore, this positive exposure emerges across different investment styles, including dedicated short, equity market neutral, long-short equity, and multi-strategy. As expected, it is especially strong among funds that pursue strategies of dedicated short and long-short equity. A positive one standard deviation increase in $INFO$ is accompanied by a 2.07% and 1.04% increase in annual returns for these two styles, respectively. This large positive covariation of hedge fund returns with the $INFO$ factor suggests that hedge fund managers can provide value because of their skill at exploiting fundamental information.

We then perform a cross-sectional analysis using a sample of 5,565 U.S. equity-oriented hedge funds over the period from February 1996 to December 2015. We start by measuring the extent to which a fund has skills in exploiting information based on historical fund returns. In this context, we define a measure we call the *fund information skill* (FIS) measure. Specifically, a hedge fund's FIS is the covariance of its returns with the $INFO$ factor. For each hedge fund, we run a time-series regression each month of the hedge funds' excess returns on the returns to the $INFO$ factor over the previous 24 months, controlling for the

[6]Again, we note that this result is not mechanical. A priori, it is possible that hedge funds perform well for reasons that are unrelated to the fundamental information contained in insider trades, short sales, and option trades. As such, our findings provide new insights regarding the sources of hedge fund performance.

market factor. The coefficient estimate on the $INFO$ factor is the fund's FIS. When hedge funds are sorted into deciles by their FIS, we find that funds in the top FIS decile earn average monthly returns approximately 0.32% higher than funds in the bottom FIS decile. This large return spread remains near 0.31% per month after we adjust for the Fung and Hsieh (2004) factors. The results are consistent with the idea that the high average returns of some funds is due, at least in part, to their skills at exploiting private information. Put differently, the results suggest that the high returns of these funds can be viewed as the returns to costly information acquisition.

Finally, we analyze the relation between funds' FIS and fund performance among different investment styles of hedge funds. We classify hedge funds into four groups according to their investment strategy (directional arbitrage, non-directional arbitrage, multi-strategy, and funds of funds) and find that FIS relates positively and significantly to hedge fund returns only for directional funds and fund of funds, but not for non-directional funds and multi-strategy funds. This finding is consistent with the notion that directional funds are more likely to aim at profiting from arbitrage opportunities through their skills in exploiting fundamental information with respect to under-value and over-value securities.

Overall, our study is the first to examine whether the past *trades* of informed market participants contain more information than past *prices* alone (e.g., Jegadeesh and Titman (1993)). We find that they do. Specifically, we are the first to construct a long-short portfolio using the information contained in insider trades, short-sales, and option trades. Unlike most prior studies that focus on one-side of informed trading, our paper combines information on both the long and short sides and presents a more complete view of the effect of informed trading activity on stock returns. The study that is closet to ours is Chen, Da and Huang (2018) who examine the performance of the net position of arbitrageurs who aim at profiting from mispricing of financial assets by combing the abnormal hedge fund holdings and short interest. We complement this study by focus on a broader base of informed agents, who are most likely to process private information about fundamental value. In the process, we show that combining the information in the long- and short-sides is important. In the process, we show that combining the information in the long- and short-sides is important. We show that the $INFO$ strategy perform significantly better than either the long- or short-leg separately. In particular, the $INFO$ factor generates a Sharpe ratio of 0.33, while the long-only and short-only portions of the $INFO$ factor have Sharpe ratios of 0.18 and -0.02, respectively. In other words, combining the information in the long and short legs provides a diversification benefit that dramatically increases the overall risk-return trade-off of these strategies. In addition, our study also contributes to the literature that examines the investment strategies and performance of hedge fund managers (e.g., Aragon and Strahan (2012); Titman and Tiu (2010); Sun, Wang, and Zheng (2011)). Our study provides new insights regarding hedge fund performance by providing evidence that at least some of the value provided by hedge fund managers derives from their skill at gathering and processing fundamental information.

The remainder of this paper proceeds as follows: Section II discusses the construction of the $INFO$ factor. Section III examines the performance of the $INFO$ factor. Section IV examines the relation between the $INFO$ strategy and hedge fund performance. Section V examines the robustness of our measure to alternate formulations. Section VI concludes.

II. INFO factor

In this section, we discuss the data used to construct the $INFO$ factor and we explain our construction methodology. We then examine the properties and performance of the $INFO$ factor.

A. Insider Data

We obtain insider trading data from Thomson Reuters. Since our measure of option trading begins in 1996, when the OptionMetrics data become available, our sample period of insider trading is from January 1996 through December 2015. Following prior studies (e.g., Cheng and Lo (2006); Huddart, Ke, and Shi (2007)), we focus on open market sale and purchase transactions by top-level managers. We sum all sales and purchases of all top-level managers for each firm-month and scale these numbers by each firm's shares outstanding from CRSP.

Following Seyhun (1992), we measure the level of insider trading for each stock each month as the net number of shares (NS) transacted, a straightforward summary of the trading activity. Let N be the number of open market sales and purchases by insiders in firm i and month t. Then:

$$NS_{i,t} = \sum_{j=1}^{N} S_{j,i,t}, \tag{1}$$

where $S_{j,i,t}$ is the number of shares for the j-th transaction (negative if the transaction is a sale) for $j = 1, \ldots, N$. So $NS_{i,t}$ simply adds the net buys in each month. We then deflate NS by the shares outstanding during the month t, denoted as SNS.[7] In addition, our results are robust to using the dollar amount of insider trades to capture the strength of trading incentives.

B. Short Interest Data

We obtain short interest data from Compustat. U.S. exchanges publicly report the quantity of short selling for each stock, each month. The data are usually compiled as of the 15th of each month and the data is then publicly reported four business days later. Our data were available to investors at each point in time, since historically these data were published in the financial press on the day following their public release from the exchanges. The Compustat short interest dataset begins in January of 1973, however we start out sample in January of 1996 since that is the first date on which option trading data becomes available. Our sample extends through December 2015. The short interest data from Compustat are

[7] In untabulated results we find qualitatively similar findings when deflating NS by the average number of shares held by all insiders over the calendar year t.

reported as the number of shares held short in a given firm. We normalize these numbers by dividing the level of short interest by each firm's shares outstanding from CRSP. We filter the data to exclude stocks with a price below $1 per share and we keep only common U.S. equities (i.e., we keep only CRSP share codes 10 and 11, so we exclude short interest data on American Depository Receipts (ADRs), Exchange Traded Funds (ETFs), and Real Estate Investment Trusts (REITs)). We also use the CRSP distribution file to exclude stock-month observations that had a share split, since the Compustat short interest data are inconsistent in their adjustment for stock splits.

C. Option Data

We obtain option data from OptionMetrics for the period from 1996 through 2015. Following Blocher and Ringgenberg (2016), we drop options with less than seven days or greater than 180 days to maturity, bid price greater than ask price, non-positive implied volatility, bid-ask spreads greater than 25%, and the absolute value of log moneyness greater than 0.3. These filters help to exclude illiquid options. Following Roll et al. (2010) and Johnson and So (2012), we use the option/stock trading volume ratio (O/S) – total option volumes scaled by total equity volumes, as our measure of option trading. Specifically, for each stock and month, we measure a firm's O/S as the ratio of aggregated trading volumes of both put and call options to total equity volume during that month.

D. Constructing the *Information Factor*

Like the momentum factor, $INFO$ is a zero-cost portfolio whose return is the difference between a long portfolio and a short one. Empirically, we first construct an aggregated information score for each stock based on the informed trading of firm insiders, short sellers, and option traders. The information score combines net insider buying as the proxy for the good news with short interest and option trading as the proxy for the bad news. Specifically, for each variable of informed trading, we assign a rank (from 1 to 100) to each stock that reflects the sorting on that given variable, where a higher rank is assigned to the value of the informed trading variable associated with a level of positive private information which results in higher abnormal returns, as reported in the literature. For example, It is documented that insider purchases predict higher future stock returns, and this result is robust to numerous measures of firm-level insider trading ((e.g., Lakonishok and Lee (2001); Jeng et al. (2003)). Therefore, we rank stocks each month by net insider buying, and those with the highest net insider buying receive the highest rank. A stock's information score ranging between 1 and 100, is the arithmetic average of its ranking percentile for each of the three information trading variables.

We construct an investable strategy, $INFO$, which is monthly returns of long–short (stock) portfolios based on the information score. Specifically, for each month, we form 10 equal-weighted portfolios of stocks sorted by their information score in the past month and then hold these portfolios for one calendar month. $INFO$ is the return spread between the decile of stocks with the highest information score (top decile) and the decile of stocks with the lowest information score (bottom decile).

E. Summary Statistics

In this subsection, we provide summary statistics on the performance of the $INFO$ factor and we compare them with those of other commonly used strategies.

[Insert Table 1 near here]

Panel A of Table 1 reports the summary statistics of the $INFO$, market portfolio (MKT), momentum factor (UMD), the Fama-French size factor (SMB), value factor (HML), profitability factor (RMW) and investment factor (CMA), as well as the Hao, Xue and Zhang (2015)'s size (ME), investment (IA) and ROE factors. The average monthly return of the $INFO$ factor from February 1996 through December 2015 is 1.331% per month, more than double the average return of any of the other factors including MKT and UMD, whose average returns are the highest among the other factors but are only 0.573% and 0.466% per month, respectively. In addition, the Sharpe ratio of the $INFO$ factor is much higher than any of the other factors. For example, the $INFO$ factor has a monthly Sharpe ratio of 0.341 (1.158 annualized), whereas the next highest Sharpe ratio is only 0.082 generated by MKT. Panel A also compares the maximum drowndown (MDD) of the $INFO$ factor with those of other well known factors. MDD is defined as the largest percentage drop in price from a peak to a bottom. In other words, it captures the maximum loss of an investor who invests in the asset at the worst time. The MDD is 14.1% for the $INFO$, lower than that of any other factor (e.g., 52.5% for MKT and 57.6% for UMD). Thus, in terms of the MDD, the $INFO$ factor performs the best as well.

In addition, Daniel and Moskowitz (2016) shows that returns generated from momentum strategies are negatively skewed with large kurtosis, implying a very fat left tail. Consistent with these results, Panel A also reports that the momentum factor has a very large negative skewness (1.5) and very large kurtosis (9.612). In contrast, the $INFO$ factor has a small positive skewness (0.052) and small kurtosis (1.212), indicating no fat tails, and thus, indicating greater chances for less volatile returns.

In Panel B of Table 1, we show the summary statistics of both the long- and short-leg of the $INFO$ factor. While the long-leg of the $INFO$ factor has an average monthly return of 1.397%, the short-leg of the $INFO$ factor has a negative average monthly return of -0.066%, suggesting that it is difficult for investors to play pure shorts as the market on average is going up during our sample period. More importantly, the $INFO$ factor delivers a much higher Sharpe Ratio and a much smaller MDD, suggesting that combining the information in the long and short legs provides a diversification benefit that dramatically increases the overall risk-return trade-off of these strategies. Overall, our evidence shows that the $INFO$ factor contains valuable information that would significantly outperform other well-known strategies.

III. Performance of the *Information Factor*

A. Comparison with the S&P 500 index

To provide further insights regarding the value of the $INFO$ strategy, we first compare the cumulative returns of the INFO factor with those of a benchmark index.[8] As benchmarks, there are numerous equity indices to choose from. We consider the S&P 500 index because it is widely used in practice and easily accessible to most investors at a low cost. For example, Vanguard S&P 500 ETF is one of the most widely used index vehicles in the U.S. equity market; it is highly liquid with low transaction costs.

[**Insert Figure 2 near here**]

Figure 2 plots cumulative returns for the $INFO$ strategy and S&P 500 benchmark index, respectively, for a one-month holding period. The two series of cumulative returns start in February 1996 and end in December 2015. As shown in the figure, investing in the $INFO$ strategy yields a cumulative return of 1960% from February 1996 to December 2015, whereas investing in the S&P 500 generates a cumulative return of only 238% over the same period. Moreover, for the $INFO$ factor, wealth increases at a much faster pace than when merely buying and holding the benchmark index after the year of 2000. In other words, the $INFO$ factor consistently outperforms the S&P 500 index after 2000. Such stable performance also suggests that the superior performance of the $INFO$ factor is not merely driven by a few outliers.

B. Performance in Subperiods

[**Insert Figure 3 near here**]

Second, the superior performance of the $INFO$ factor is quite stable over time. Fig. 2 plots the average returns of the $INFO$ factor for every five-year window over 1996 to 2015.

[8] As our baseline, we assume that an investor would invest in a standard index fund.

Comparing to the market, the $INFO$ factor significant outperform the market in every five-year window before 2011, while it slightly outperforms the market in the five-year window from 2011 to 2015. In contrast, the momentum factor underperforms the market after 2005. In addition, the $INFO$ factor outperforms the momentum every five-year window as well.

C. Alphas

The previous sections found that the $INFO$ factor earns consistently large returns. However, it remains possible that the return on the $INFO$ strategy can be explained by exposure to other common risk factors. To address this concern, we adjust for risk factor exposures with three asset pricing models: (1) the Fama-French (1993) three factor model augmented with Pastor and Stambaugh (2003) liquidity factor ("FF3+LIQ") model; (2) the Fama-French (2015) five-factor ("FF5") model; (3) the HXZ (2015) q-factor (HXZ) model. Table 2 reports alphas and risk loadings for the $INFO$ factor and momentum factor, with respect to the three asset pricing models, respectively. As shown in Table 2, the $INFO$ factor has a FF3+LIQ alpha of 1.294%, a FF5 alpha of 1.259% per month, and a HXZ alpha of 1.306% per month. These results are only slightly lower than the unadjusted average return (1.237% per month in Table 1), suggesting that the $INFO$ factor is not loading on systematic risk. In contrast, the momentum factor has a FF3+LIQ alpha of 0.714%, a FF5 alpha of 0.479% per month, and a HXZ alpha of 0.046% per month, which are significantly lower than those of the $INFO$ factor.

[Insert Table 2 near here]

In addition, Schwert (2003) finds that, unlike most anomalies, momentum is robust even after its publication in academic articles. In addition, the momentum factor also passes the hurdle proposed by Harvey and Liu (2015) to detect false discoveries. Interestingly, in our sample period, the alpha of the momentum factor has a t-statistic of 2.30 with respect to the FF3+LIQ model while it has an insignificant t-statistic of 1.38 and 0.14, respectively, for the FF5 model and HXZ model. In contrast, the alpha of the $INFO$ factor has a t-statistic of 5.62, 5.23 and 5.13 with respect to the FF3+LIQ model, FF5 model and HXZ model, respectively. Hence, the $INFO$ factor appears to be more statistically significant than the well-known momentum factor, and it easily exceeds the hurdle proposed by Harvey and Liu (2015) to detect false discoveries.

D. Mean-Variance Spanning Tests

Our $INFO$ score uses information on insider trading, short interest, and option trading. Since the information from these three types of trades is publicly available, it is an interesting question as to whether a portfolio of the commonly used factors can replicate the performance of the $INFO$ strategy. In other words, can the $INFO$ strategy outperform a portfolio of the common factors in the literature?

In this section, we explore whether the $INFO$ factor lies outside the mean-variance frontier of the common risk factors, which is sufficient to show that the $INFO$ outperforms a portfolio of these factors. Huberman and Kandel (1987) are the first to provide a mean-variance spanning test on the hypothesis of whether N assets can be replicated in the mean-variance space by a set of K benchmark assets. It has been widely applied in recent studies to test the same hypothesis (e.g.,De Roon, Nijman, and Werker (2001), Korkie and Turtle (2002), Kan and Zhou (2012), and Han, Zhou, and Zhu (2016)). To do so, we run a regression of the $INFO$ factor on a portfolio of well known factors – the FF3+LIQ factors, FF5 factors, or HXZ factors:

$$r_{INFO,t} = \alpha_0 + \sum_{i=1}^{n} \beta_i r_{f_{i,t}} + \epsilon_t, \tag{2}$$

where $r_{INFO,t}$ is the monthly return on the $INFO$ factor and $r_{f_{i,t}}$ represents the monthly return on factor i in each replicating portfolio.

The spanning hypothesis is equivalent to the following parametric restrictions on the model:

$$H_0 : \alpha = 0, \sum_{i=1}^{n} \beta_i = 1. \tag{3}$$

Following Kan and Zhou (2012) and Han et al. (2016), we run six spanning tests: (1) Wald test under conditional homoskedasticity, (2) Wald test under independent and identically distributed (IID) elliptical distribution, (3) Wald test under conditional heteroskedasticity, (4) Bekerart-Urias spanning test with errors-in-variables (EIV) adjustment, (5) Bekerart-Urias spanning test without the EIV adjustment, and (6) DeSantis spanning test. All six tests have asymptotic chi-squared distribution with 2N (N=1) degrees of freedom.

[**Insert Table 3 near here**]

Table 3 presents the spanning test results for the FF3+LIQ factors, FF5 factors, and HXZ factors. For each factor model, all six tests reject the null hypothesis that the $INFO$ factor is inside the mean-variance frontier of the factors. In other words, the results suggest that the $INFO$ factor expands the frontier relative to other well-known factors. Overall, the $INFO$ factor is a unique factor that cannot be replicated by well known factors and thus, performs far better than the Fama-French factors and HXZ q-factors.

E. Sharpe (1988) Style Regressions

In the previous subsection, we show that the $INFO$ factor outperforms any portfolio of the Fama-French factors and HXZ q-factors. In this subsection, we ask a different but related question as to how the performance of the $INFO$ factor is related to the Fama-French factors and HXZ q-factors. To answer this question, we conduct a Sharpe (1988) style analysis on the $INFO$ factor.

Sharpe (1988) style analysis is widely used in fund performance analysis to identify the contribution of various style portfolios to a given fund. In our case, we regress the $INFO$

factor on the FF3 factors, FF3+LIQ factors, and HXZ q-factors, respectively, according to the model:

$$r_{INFO,t} = \alpha_0 + \sum_{i=1}^{n} \beta_i r_{f_{i,t}} + \epsilon_t \tag{4}$$

subject to the constraints:

$$\beta_i >= 0 \tag{5}$$

$$\sum_{i=1}^{n} \beta_i = 1, \tag{6}$$

where $r_{INFO,t}$ is the monthly return on the $INFO$ factor and $r_{f_{i,t}}$ represents the monthly return on factor i in each replicating portfolio.

[Insert Table 4 near here]

Table 4 presents the results of the style regressions for the Fama-French three factors, Fama-French three factors and liquidity factor, and HXZ q-factors, respectively. For Fama-French three factors, the MKT factor explains about 14% of the movements of the $INFO$ factor, the SMB 35.5%, and HML 50.5%. Compared to the performance of the MKT factor, the performance of SMB and HML plays a relatively important role in explaining the performance of the $INFO$ factor. In other words, the superior performance of the $INFO$ factor is largely attributed to the performance of small stocks and growth stocks. This result is consistent with the idea that small firms and growth firms are subject to higher information asymmetries and thus informed traders have relatively larger informational advantage in these stocks, which then generates higher profits. For example, a large stock with low growth expectations (i.e., a large capitalization value stock) is less likely to have information asymmetries regarding its fundamental value. On the other hand, a small high growth stock is likely to have high uncertainty regarding its fundamental value, thereby providing more room for asymmetrically informed investors to profit. For Fama-French three factors augmented with the liquidity factor, the MKT factor accounts for 8.1% of the movements of the $INFO$ factor, the SMB 35.7%, HML 41.9%, and LIQ 14.3%. For HXZ q-factors, the MKT factor accounts for 13.7% of the movements of the $INFO$ factor, the ME 19.3%, IA 31.8%, and ROE 35.2%. Hou et al. (2015) suggest that the investment factor (IA) is closely related the HML factor. Thus, these results are also consistent with the idea that the $INFO$ factor performance is attributable to information advantage in growth stocks.

F. Characteristics of Decile Portfolios

[Insert Table 5 near here]

Table 5 reports the average returns and characteristics of decile portfolios sorted by the information score. The average next-month returns increase monotonically from the decile with the lowest information score (Low) to the decile with the highest information score (High). More specifically, stocks with the highest information score have the highest return in the subsequent month, about 1.397% per month, whereas stocks with the lowest information factor yield the lowest average return in the subsequent month, only about 0.066% per month. Interestingly, the prior month returns (Ret[-1]), past six-month cumulative returns(Ret[-2, -6]), and past sixty-month cumulative returns(Ret[-25, -60]), decrease monotonically across the deciles. The market size displays a hump shape across the quintiles both deciles Low and High have smaller market size than the other deciles, while the book-to-market (B/M) ratio increase monotonically across the deciles. Idiosyncratic volatility (IVol) displays a relatively stable pattern across the deciles even though deciles 1 and 2 have a higher idiosyncratic volatility. We also report the Amihud (2002)s illiquidity and share turnover rate, both of which measure the liquidity of stocks. The high decile exhibits a much higher Amihud (2002)s illiquidity than other deciles and share turnover rate decreases monotonically across the deciles.

G. Risk or Characteristics?

The $INFO$ score earns consistently large returns and large alphas relative to known systematic risk factors. Accordingly, we next examine whether the superior performance of $INFO$ strategy represents compensation for exposure to another source of systematic risk (potentially not captured by existing measures). To investigate this issue, following Daniel and Titman (1997), we perform double sorts by first sorting stocks into quintiles based on one of their characteristics: the level of short interest, the level of option trading, or the level of insider trading, and then sorting into quintiles based on their loadings on $INFO$ factor. Each stock's loading on the $INFO$ factor is estimated by regressing the stock returns on the $INFO$ factor and Fama-French (1997) three-factors over a 24-month rolling window. We require that funds have at least 18 return observations during the 24-month rolling window. Specifically, we estimate the following regression:

$$Ret_{i,t} = \alpha_0 + \alpha_1 INFO_t + \alpha_2 MKT_t + \alpha_3 SMB_t + \alpha_4 HML_t + \epsilon_{i,t}, \tag{7}$$

where $Ret_{i,t}$ is the monthly return on stock i in excess of the one-month T-bill return, $INFO$ is the $INFO$ factor in month t, and α_1 captures stock i's loading on the $INFO$ factor. In addition, we control for the Fama-French three-factors.

[Insert Table 6 near here]

To further understand whether the return on the $INFO$ is either driven by the return to short sellers' private negative news, which is proxied by the level of short interest (SR), or systematic risk exposure, we perform double sorts by first sorting into quintiles based on SR and then sorting into quintiles based on $INFO$ loadings. Panel A of Table 5 presents the results. Across quintiles of SR, the spreads in Fama-French three-factor alphas between the top and bottom $INFO$-loading quintiles are small and statistically insignificant, ranging from -0.03% to 0.20% per month.

Next, we perform double sorts by first sorting into quintiles based on the level of option trading (OS), which captures option traders' private information, and then sorting into quintiles based on $INFO$ loadings. Panel B of Table 5 presents the results. Across quintiles of OS, the spreads in Fama-French three-factor alphas between the top and bottom $INFO$-loading quintiles are statistically insignificant, ranging from -0.25% to 0.16% per month.

Finally, we perform double sorts by first sorting into quintiles based on the level of net insider buy orders (IN), which proxies for fundamental good news, and then sorting into quintiles based on $INFO$ loadings. Panel C of Table 5 presents the results. Again, across quintiles of IN, the spreads in Fama-French three-factor alphas between the top and bottom $INFO$-loading quintiles are statistically insignificant, ranging from -0.12% to 0.37% per month.

Overall, our results show that after controlling for each stock's level of short interest, option trading, and insider trading, there is not a statistically significant relation between each stock's return and its loading on the $INFO$ factor. In other words, the results show that the returns to the $INFO$ factor are driven by the characteristics within each stock, and *not* exposure to systematic risk. In other words, the $INFO$ is not a systematic risk factor. As such, the large abnormal returns to the $INFO$ strategy can be viewed as a measure of the returns to costly information acquisition by informed traders.

IV. INFO Strategy and Hedge Fund Performance

The $INFO$ strategy earns large abnormal returns that do not appear to be compensation for systematic risk. Rather, the returns measure the compensation for the cost of acquiring and processing information. Accordingly, in this section, we next test whether the $INFO$ factor can explain the returns of hedge funds. We first describe our sample of hedge funds, and then we provide detail regarding our methodology for estimating hedge funds' skills in exploiting fund information skill (FIS). Finally, we explore the relation between hedge funds' FIS and performance.

A. Hedge Fund Data

We obtain individual hedge fund data from the Lipper TASS database. TASS classifies hedge funds into 11 self-reported style categories: convertible arbitrage, dedicated short bias, emerging markets, event driven, equity market neutral, fixed income arbitrage, funds of funds, global macro, long/short equity hedge, managed futures, and multi strategy. Since we focus on the trading activity of informed agents in U.S. equity and option markets, we only include U.S. equity-oriented hedge funds and drop global macro, emerging markets, fixed income arbitrage, and managed futures.

Following prior research, we apply several screens to the TASS hedge fund data. First, to address the concern that hedge funds may backfill returns when newly added to the database, we exclude the first 12 months of returns for each fund. Second, we only include funds that report monthly net-of-fee returns in U.S. dollars and allow for redemption at a monthly or higher frequency. Third, we delete duplicate funds from the sample and exclude funds with assets under management (AUM) of less than \$5 million. Finally, we require each fund to have at least 24 return observations. Our final sample contains 5,565 hedge funds over the period from February 1996 to December 2015.

B. INFO Strategy and Hedge Fund Returns: Time-Series Analysis

In the section, we focus on time-series analyses examining the relation between hedge fund style returns and their exposures to the $INFO$ factor. For each fund investment style, we calculate the asset-weighted hedge fund returns weighted by funds monthly assets under management (AUM) as the aggregated fund style returns. Our starting benchmark is the Fung and Hsieh (2004) seven-factor model. To capture the links between hedge fund index returns, hedge fund strategies, and their exposure to the $INFO$ factor, we extend the seven factor model to a ten-factor model incorporating the $INFO$ factor ($INFO$), momentum factor (UMD), and liquidity factor (LIQ) according to the model:

$$
\begin{aligned}
Ret_{i,t} = \alpha_0 + \alpha_1 INFO_t + \alpha_2 MKT_t + \alpha_3 SMB_t + \alpha_4 PTFSBD_t + \alpha_5 PTFSFX_t + \\
\alpha_6 PTFSCOM_t + \alpha_7 \Delta TERM_t + \alpha_8 \Delta CREDIT_t + \alpha_9 UMD_t + \alpha_{10} LIQ_t + \epsilon_{i,t},
\end{aligned} \tag{8}
$$

where $Ret_{i,t}$ is the monthly return on hedge fund index i in excess of the one-month T-bill return and $INFO$ is the $INFO$ factor in month t, as defined in Section II. In addition, we control for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.

[Insert Table 7 near here]

We examine seven hedge Fund investment styles, including Convertible Arbitrage, Dedicated Short, Event Driven, Equity Market Neutral, Multi-Strategy, Long/Short Equity, and Funds of Funds, which cover the major equity-oriented hedge fund strategies.

Table 7 presents loadings on the 10 risk factors in equation 8 for the above styles as well as the aggregate hedge fund index during the whole sample period. The R-squared of the ten-factor model range from 25.9% for the Convertible Arbitrage to 80.9% for the Long/Short Equity. For the aggregate hedge fund index, a one-standard deviation increase in the $INFO$ exposure is associated with an increase in hedge fund returns of 0.036% per month, or 0.432% per year. Although the result is modest in magnitude, the effect is statistically significant. Moreover, we note that the overall index includes a wide-variety of funds that may not be exposed to the $INFO$ factor. Accordingly, we next analyze seven styles of hedge funds and find that four styles exhibit significantly positive $INFO$ loadings over our sample period from February 1996 to December 2015, including Dedicated Short, Market Neutral, Long/Short Equity, and Multi-Strategy. The results here are consistent with In terms of magnitudes, returns to hedge funds that invest in Dedicated Short and those that pursue Long/Short Equity strategies are particularly sensitive to the $INFO$ factor. For example, a one-standard deviation increase in the $INFO$ factor is associated with an increase in returns of 0.173% per month for hedge funds investing in Dedicated Short; and for hedge funds that engage in Long/Short Equity investing, the corresponding number is 0.087% per month.

C. Cross-Sectional Relational between the INFO and Hedge Fund Returns

In this section, we employ the portfolio sorting approach to test the effect of hedge funds' skills in exploiting fund information (FIS) on next-month fund performance in the cross section. Starting with February 1996, we form 10 equal weighted hedge fund portfolios sorted on the basis of their FIS for each month. Each fund's FIS is estimated by regressing the fund's excess returns on the $INFO$ factor and the market factor over a 24-month rolling window. We require that funds have at least 18 return observations during the 24-month rolling window. We estimate the following regression:

$$Ret_{i,t} = \alpha_0 + \alpha_1 INFO_{i,t} + \alpha_2 MKT_{i,t} + \epsilon_{i,t}, \tag{9}$$

where the dependent variable $Ret_{i,t}$ is the return of fund i in month t, $INFO$ is the information factor in month t, which is defined in Section II, and α_1 captures fund i's FIS.

We examine the performance of hedge fund FIS deciles over the next month after portfolio formation. Besides excess returns of hedge funds, we measure alphas by regressing the time series of the excess returns of each decile portfolio on the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.

[Insert Table 8 near here]

Table 8 reports the results for hedge fund performance across FIS deciles. The portfolio sorts show a positive relation between hedge funds' FIS and next-month average returns. The high-FIS portfolio (decile 10) delivers an excess return of 0.587% per month and an alpha of 0.322% per month, while the portfolio with the lowest FIS (decile 1) shows an excess return of 0.267% per month and an alpha of 0.008% per month. The return spread between these two extreme portfolios is 0.319% per month with a t-statistic of 2.56, and the spread in alpha between the two portfolios is 0.314% per month with t-statistic of 3.01. Thus, the results from both time-series analyses and portfolio sorts suggest that hedge fund managers who either have better skills in exploiting the private information of other informed traders (insiders, short sellers, and option traders) or have the same latent signals about fundamental value display superior performance.

D. Hedge Fund Style Analysis

Finally, we analyze the effect of funds' FIS in explaining the variation in hedge fund returns for each different investment style. Given the diversity of hedge funds investment strategies and the fact that not every fund aims to exploit arbitrate opportunities, we expect to observe cross-sectional heterogeneities in funds' FIS across different investment styles. There are several fund styles that are used by only a few funds; as a result, our tests may lack the power to detect evidence of a statistically significant effect for these styles. For example, monthly decile portfolios of funds in convertible arbitrage, dedicated short bias, and equity market neutral contain below 10 funds on average. Thus, following Agarwal, Daniel, and Naik (2009), we further classify hedge funds into four groups according to their investment strategy: directional arbitrage (i.e., long/short equity and dedicated short bias funds), nondirectional arbitrage (i.e., convertible arbitrage, event driven, and equity market neutral funds), multi-strategy, and funds of funds.

[Insert Table 9 near here]

Table 9 presents the results. For funds in each investment group, we sort funds into deciles based on their FIS and evaluate next-month's equal-weighted fund return. The results are striking. First, we observe that directional funds have a larger variation in FIS than other types of funds. Second, we find that FIS relates positively and significantly to hedge fund returns for directional funds and multi-strategy funds but not for nondirectional funds and funds of funds. Specifically, for directional hedge funds, the return spread between the top and bottom FIS deciles is 0.445% per month, with a t-statistic of 3.11, and the spread in alpha is 0.434% per month, with t-statistic of 2.99. These findings are consistent with the idea that, unlike nondirectional funds and funds of funds, directional funds and multi-strategy generally aim at profiting from exploiting private information with respect to under-valued and over-valued securities. Overall, our results suggest that skilled hedge fund managers earn substantial returns, in part, because of their skill in acquiring and processing information.

V. Robustness checks

In this section, we show that the superior performance of the $INFO$ factor is robust to use the value-weighted measure as a robustness check. We estimate the raw return and alpha of the value-weighted $INFO$ factor and present results in Table 10.

[**Insert Table 10 near here**]

Panel A of Table 10 shows that the value-weighted $INFO$ factor has a slightly lower average return of 1.252% per month instead of 1.331% per month. In addition, the standard deviation is slightly higher (4.713%), and the Sharpe ratio is slightly lower (0.225) compared to our main result of 0.334. However, comparing to other factors, the value-weighted $INFO$ factor still delivers the highest average return and Sharpe ratio. For example, the value-weighted $INFO$ has a Sharpe ratio of 0.225, more than quadrupling that of the momentum factor and doubling that of the market portfolio.

In Panel B, Table 10, we find that the value-weighted $INFO$ has an alpha of 1.089%, 1.064% and 1.055% per month with respect to the FF3+LIQ factor, FF5 factor, and HXZ model, respectively, which are only slightly lower than those reported in Table 2 (1.277%, 1.135% and 1.287%). Overall, the $INFO$ factor is highly robust to alternate formulations.

VI. Conclusion

We propose an information trading strategy based on the informed stock buying of firm insiders and the informed stock selling of short sellers and option traders. In contrast to the popular momentum strategy that relies on past prices, our information strategy is based on past trades and has twice the average return of momentum. The performance of the information strategy is robust to different factor models. From an asset pricing perspective, we find that the information factor does predict returns, however it does *not* appear to be compensation for systematic risk. Rather, it captures the returns to costly information acquisition and processing. Moreover, we explore whether some hedge funds have skill in exploiting private information about firm fundamentals. We find that they do. We measure fund information skills (FIS) using the covariation between fund returns and the information factor, and find that high-FIS funds on average outperform low-FIS funds by 0.43% per month on a risk-adjusted basis. These results are consistent with the notion that the skill in generating and processing private information is an important source of hedge fund returns.

Overall, our study highlights the importance of combining positive signals with negative signals. Future research should explore the value of such information in other asset markets, such as bonds, currencies, or commodities.

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Figure 1. *INFO* Factor Monthly Returns

This figure plots the time series of $INFO$ factor returns from February 1996 to December 2015. We first construct an information score for each stock in each month based on the informed trading of firm insiders, short sellers, and option traders. Specifically, for each measure of informed trading, we assign a rank (from 1 to 100) to each stock, where a higher rank is assigned to the value of the informed trading variable associated with a level of positive private information. A stock's information score is the arithmetic average of its ranking percentile for each of the three information trading variables. The $INFO$ factor is the return spread between the decile of stocks with the highest information score and the decile of stocks with the lowest information score.

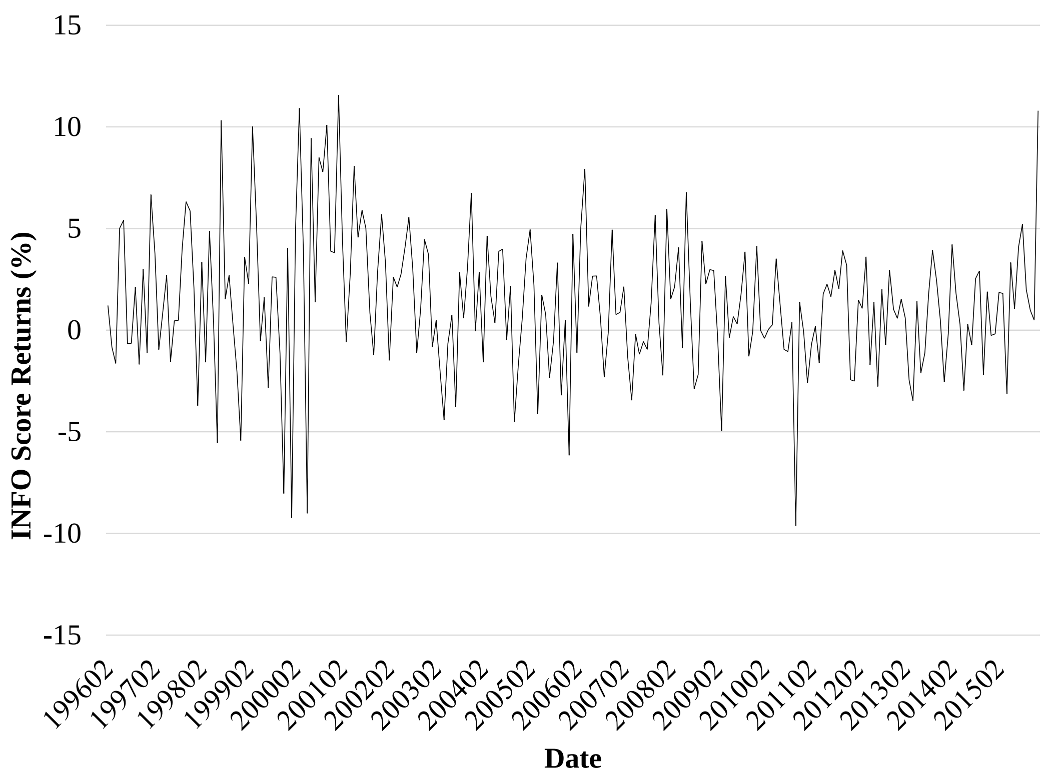

Figure 2. Compound Returns in Event Time for *INFO* Factor

The figure plots compound returns in the event time (from February 1996 to December 2015) for the $INFO$ factor. We first construct an information score for each stock in each month based on the informed trading of firm insiders, short sellers, and option traders. Specifically, for each measure of informed trading, we assign a rank (from 1 to 100) to each stock, where a higher rank is assigned to the value of the informed trading variable associated with a level of positive private information. A stock's information score is the arithmetic average of its ranking percentile for each of the three information trading variables.The $INFO$ factor is the return spread between the decile of stocks with the highest information score and the decile of stocks with the lowest information score.

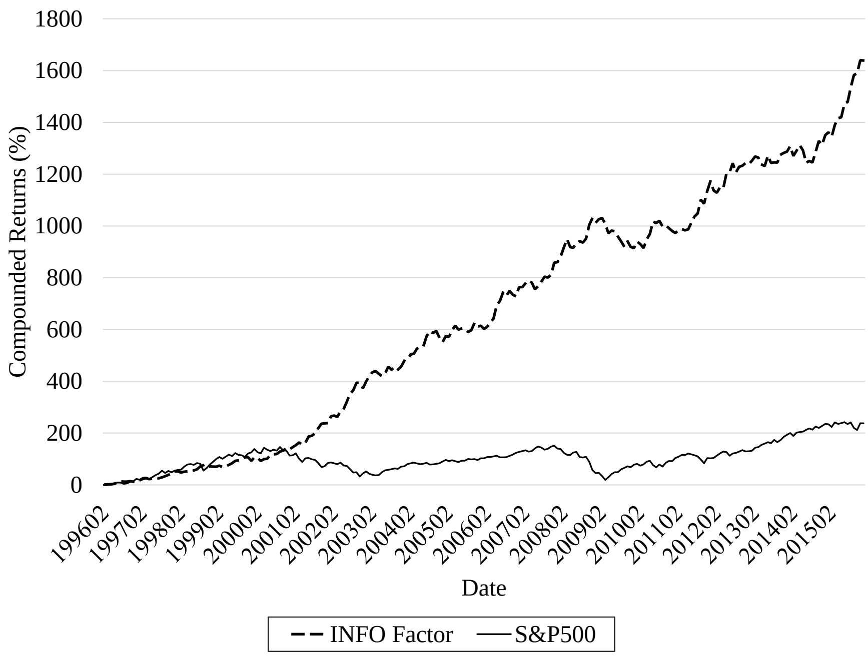

Figure 3. Performance of *INFO* Factor Across Subperiods

This figure plots the average monthly returns of the $INFO$ factor, the market, and the momentum factor over roughly for every five-year window from 1996 to 2015. The first period is from June 1996 to December 2000, the second is from January 2001 to December 2005, the third is from January 2006 to December 2010, and the last is from January 2011 to December 2015.

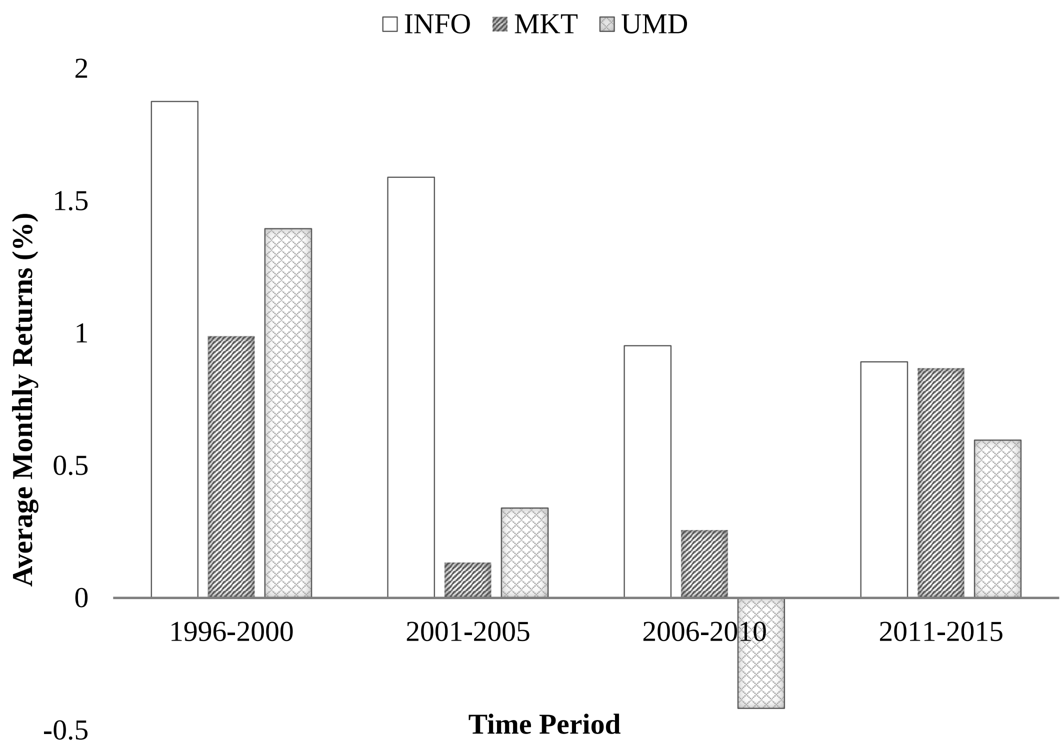

Table I
Summary Statistics for *INFO* Factor

Panel A reports summary statistics for the information Factor ($INFO$), the market factor (MKT), the momentum factor (UMD), the size factor (SMB), the value factor (HML), the profitability factor (RMW) and the the investment factor (CMA), the HXZ (2015) size factor (ME), the HXZ (2015) investment factor (IA), and the HXZ (2015) ROA factor (ROA) For each strategy, we report the mean (in percent), standard deviation (in percent), Sharpe ratio, minimum return (in percent), skewness, and kurtosis for the entire sample period from February 1996 to December 2015.

Factor (1)	Mean (2)	Standard Deviation (3)	Sharpe Ratio (4)	Minimum Return (5)	Maximum Drawdown (6)	Skewness (7)	Kurtosis (8)
Panel A: INFO and Other Factors							
INFO	1.331	3.413	0.334	-9.624	0.141	0.052	1.212
MKT	0.573	4.599	0.082	-18.541	0.525	-0.737	1.279
UMD	0.466	5.389	0.050	-34.580	0.576	-1.500	9.612
SMB	0.236	3.330	0.012	-15.360	0.397	0.483	5.411
HML	0.180	3.307	-0.005	-13.110	0.452	0.046	3.085
RMW	0.350	2.842	0.054	-17.570	0.392	-0.521	8.875
CMA	0.265	2.213	0.031	-6.810	0.153	0.667	2.306
ME	0.311	3.419	0.033	-14.392	0.386	0.847	7.270
IA	0.261	2.139	0.030	-7.157	0.161	0.372	1.879
ROE	0.381	2.991	0.062	-13.852	0.299	-0.701	4.227
Panel B: Long- and Short-leg of INFO Factor							
Long	1.397	6.455	0.187	-22.931	0.460	-0.590	2.127
Short	0.066	5.214	-0.024	-25.374	0.749	-0.469	0.920

Table II
Fama-French and HXZ Alphas

The table reports risk adjusted returns (alphas) and risk loadings with respect to the FF3+LIQ model, the FF5 model, and the HXZ model, respectively, for the $INFO$ factor and the UMD factor. The alphas are reported in percentage. t-statistics calculated using Newey and West (1987) standard errors are in parentheses below the coefficient estimates. Significance at the 1%, 5%, and 10% levels is given by ***, **, and *, respectively. The sample period is from February 1996 through December 2015.

Explanatory	FF3+LIQ factor		FF5 factor		HXZ factor	
Variable	INFO	UMD	INFO	UMD	INFO	UMD
	(1)	(2)	(3)	(4)	(5)	(6)
MKT	-0.049	-0.421***	-0.015	-0.303***	-0.031	-0.108
	(-0.97)	(-4.26)	(-0.26)	(-3.03)	(-0.46)	(-1.33)
SMB	0.010	0.131	0.083	0.199		
	(0.10)	(0.85)	(0.86)	(1.19)		
HML	0.072	-0.379**	0.018	-0.697***		
	(0.92)	(-2.23)	(0.16)	(-3.51)		
LIQ	0.079	0.058				
	(1.57)	(0.50)				
RMW			0.194	0.329*		
			(1.38)	(1.72)		
CMA			-0.039	0.492		
			(-0.24)	(1.50)		
ME					0.030	0.509***
					(0.34)	(3.54)
IA					0.017	-0.399
					(0.13)	(-1.65)
ROE					0.073	1.087***
					(0.59)	(4.77)
Alpha	1.294***	0.714**	1.259***	0.479	1.306***	0.046
	(5.62)	(2.30)	(5.23)	(1.38)	(5.13)	(0.14)
Obs.	239	239	239	239	239	239
Adj. R-squared	0.017	0.146	0.022	0.172	0.008	0.355

Table III
Mean-Variance Spanning Tests

The table reports the results of tests examining whether the $INFO$ factor can be spanned by the factors of the FF3 model, the FF5 model, or the HXZ model. W is the Wald test under conditional homoskedasticity, We is the Wald test under the IID elliptical, Wa is the Wald test under the conditional heteroskedasticity, *J1* is the Bekaert-Urias test with the Errors-in-Variables (EIV) adjustment, *J2* is the Bekaert-Urias test without the EIV adjustment, and *J3* is the DeSantis test. All six tests have an asymptotic chi-squared distribution with 2N(N=1) degrees of freedom. p-values are shown below the test statistics in parentheses. The sample period is from February 1996 through December 2015.

Factors	W	We	Wa	*J1*	*J2*	*J3*
FF3+LIQ-factor	93.46	59.41	106.49	49.83	50.19	66.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FF5-factor	33.42	25.03	29.65	24.00	27.22	32.96
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HXZ-factor	40.97	28.71	28.03	22.34	25.30	30.25
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table IV
Sharpe Style Regressions

The table reports results from Sharpe (1988) style regressions. Regression results are reported for the FF3 model, the FF3+LIQ model and the HXZ model. For each regression, the slope coefficients are restricted to be positive and their sum is restricted to equal one. t-statistics calculated using Newey and West (1987) standard errors are in parentheses below the coefficient estimates. Significance at the 1%, 5%, and 10% levels is given by ***, **, and *, respectively. The sample period is from February 1996 through December 2015.

	FF3 factors	FF3+LIQ factors	HXZ factors
	(1)	(2)	(3)
MKT	0.140**	0.081	0.137***
	(2.12)	(1.26)	(2.67)
SMB	0.355***	0.357***	
	(4.47)	(3.58)	
HML	0.505***	0.419***	
	(8.32)	(6.75)	
LIQ		0.143*	
		(1.79)	
ME			0.193***
			(2.88)
IA			0.318***
			(3.03)
ROE			0.352***
			(4.27)

Table V
Characteristics of the *INFO* Score Decile Portfolios

This table reports the average return and characteristics of the INFO Score decile portfolios. The INFO score is constructed for each stock in each month based on the informed trading of firm insiders, short sellers, and option traders. Specifically, for each measure of informed trading, we assign a rank (from 1 to 100) to each stock, where a higher rank is assigned to the value of the informed trading variable associated with a level of positive private information. A stock's INFO score is the arithmetic average of its ranking percentile for each of the three information trading variables. Market size (MVE) is in millions of dollars. BM is the book-to-market ratio. Ret[+1](%), Ret[-1](%), Ret[-2,-6](%), and Ret[25,60](%) are subsequent month return, prior month return, past 6-month cumulative return skipping the last month, past 60-month cumulative return skipping the last 24 months, respectively. IVol(%) is the idiosyncratic volatility relative to the Fama-French three-factor model estimated from the daily returns of each month. Illiquidity is the monthly Amihud (2002)s illiquidity. Turnover(%) is the monthly turnover rate of the stocks. The sample period is from February 1996 through December 2015.

Decile	Ret[+1]	MVE	BM	Ret[-1]	Ret[-2, -6]	Ret[-25, -60]	IVol	Illiq	Turnover
1 (Low)	0.066	4361.05	0.367	3.743	14.453	120.443	0.024	0.003	35.452
2	0.642	6987.08	0.414	2.638	10.736	97.479	0.021	0.003	27.413
3	0.793	9965.62	0.421	1.880	8.858	87.409	0.020	0.003	23.488
4	0.640	12973.49	0.433	1.852	8.400	77.145	0.018	0.003	19.973
5	0.861	15670.99	0.444	1.638	7.568	67.577	0.017	0.003	17.792
6	1.075	16064.12	0.454	1.187	7.322	63.481	0.017	0.004	16.156
7	0.901	13278.39	0.468	1.132	6.998	59.667	0.017	0.004	14.906
8	1.036	8316.03	0.492	1.033	6.768	52.095	0.016	0.005	13.756
9	1.297	4749.89	0.519	0.782	6.223	47.926	0.016	0.007	12.697
10 (High)	1.397	2670.14	0.558	0.261	5.580	39.535	0.017	0.014	10.777

Table VI
Monthly Fama-French Three-Factor Alphas from Portfolios Formed by Conditioning on Short Interest, Option Trading, and Insider Trading

The table contains monthly FF Alphas (in percent) for portfolios over the period February 1996 through December 2015. Each month, portfolios are formed by first sorting into quintiles using the previous month's short interest (Panel A), option trading (Panel B), or insider trading (Panel C) and then sorting into quintiles using the previous month's $INFO$ loading. These equal-weighted portfolios are then held for one calendar month. t-statistics are shown below the portfolio alphas in parentheses.

			INFO loading					
			1 (Low)	2	3	4	5 (High)	High-Low
Panel A: Monthly FF 3-Factor Alphas for Short Interest Portfolios								
Short Interest	1 (Low)	0.902	0.732	0.985	0.870	1.047	0.146	
			(2.57)	(2.23)	(2.96)	(2.54)	(2.61)	(0.88)
	2		0.718	0.738	0.798	0.780	0.922	0.204
		(1.84)	(2.08)	(2.27)	(2.12)	(2.01)	(1.05)	
	3		0.793	0.531	0.728	0.730	0.789	-0.004
			(1.84)	(1.37)	(1.90)	(1.84)	(1.60)	(-0.02)
	4		0.765	0.624	0.498	0.724	0.740	-0.025
			(1.66)	(1.59)	(1.27)	(1.60)	(1.54)	(-0.10)
	5 (High)		0.232	0.252	0.328	0.219	0.199	-0.033
			(0.45)	(0.52)	(0.72)	(0.47)	(0.36)	(-0.12)
Panel B: Monthly FF 3-Factor Alphas for Option Trading Portfolios								
Insider Trading	1 (Low)		0.945	0.673	0.788	0.878	0.695	-0.250
			(2.16)	(1.83)	(2.12)	(2.33)	(1.54)	(-1.13)
	2		0.841	0.805	0.998	0.626	0.811	-0.030
			(1.93)	(2.14)	(2.79)	(1.58)	(1.68)	(-0.14)
	3		0.774	0.645	0.864	0.642	0.935	0.161
			(1.80)	(1.70)	(2.27)	(1.61)	(1.81)	(0.65)
	4		0.361	0.701	0.605	0.581	0.520	0.159
			(0.77)	(1.83)	(1.60)	(1.42)	(1.05)	(0.65)
	5 (High)		0.353	0.047	0.389	0.753	0.414	0.061
			(0.75)	(0.11)	(1.01)	(1.80)	(0.80)	(0.24)
Panel C: Monthly FF 3-Factor Alphas for Insider Trading Portfolios								
Insider Trading	1 (Low)		0.560	0.448	0.543	0.533	0.443	-0.117
			(1.36)	(1.18)	(1.49)	(1.37)	(0.98)	(-0.55)
	2		0.546	0.637	0.484	0.288	0.494	-0.052
			(0.26)	(1.61)	(1.03)	(0.62)	(0.84)	(-0.44)
	3		0.537	0.402	0.609	0.675	0.601	0.064
			(1.21)	(0.97)	(1.60)	(1.70)	(1.18)	(0.31)
	4		0.538	0.421	0.884	0.306	0.903	0.365
			(1.27)	(1.21)	(2.07)	(0.80)	(1.76)	(1.00)
	5 (High)		0.9199	0.861	0.918	0.999	1.093	0.173
			(2.06)	(2.24)	(2.52)	(2.54)	(2.31)	(0.87)

Table VII

***INFO* Factor and Hedge Fund Returns: Time-Series Analysis**

The table presents the results of time-series regressions of hedge fund style returns on the $INFO$ factor, the Fung and Hsieh (2004) seven-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. We focus on Hedge Fund styles including Convertible Arbitrage, Dedicated Short, Emerging Market, Equity Market Neutral, Event Driven, Distressed Arbitrage, Event Multi-Strategy, Risk Arbitrage, Long/Short Equity, Managed Futures, and Multi-Strategy indexes. t-statistics are in parentheses below the coefficient estimates. Significance at the 1%, 5%, and 10% levels is given by ***, **, and *, respectively. Our sample period is from February 1996 to December 2015.

	Dependent Variable: Hedge fund index return (monthly)							
	All	Convertible Arbitrage	Dedicated Short	Event Driven	Market Neutral	Long Short	Multi-Strategy	Funds of Funds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INFO	0.036**	0.019	0.173***	0.028	0.036**	0.087**	0.046*	0.003
	(2.25)	(0.60)	(3.02)	(1.31)	(2.35)	(2.58)	(1.75)	(1.62)
MKT	0.071***	0.065**	-0.571***	0.171***	0.071***	0.408***	0.157***	0.198***
	(5.68)	(2.13)	(-10.43)	(10.28)	(5.05)	(17.76)	(9.34)	(9.23)
SMB	0.018	0.059**	-0.272***	0.085***	0.003	0.152***	0.041*	0.060**
	(1.29)	(2.00)	(-4.34)	(3.79)	(0.28)	(6.15)	(1.89)	(2.58)
PTFSBD	-0.005	-0.008	-0.003	-0.015***	-0.001	0.000	-0.002	-0.005
	(-1.50)	(-1.55)	(-0.28)	(-3.09)	(-0.38)	(0.02)	(-0.53)	(-1.05)
PTFSFX	0.002	-0.002	-0.013	0.005	0.005*	0.008	0.002	0.012***
	(0.90)	(-0.50)	(-1.22)	(1.40)	(1.92)	(1.56)	(0.53)	(2.66)
PTFSCOM	-0.004	-0.005	-0.009	-0.007	-0.001	-0.002	-0.004	0.003
	(-1.07)	(-0.68)	(-0.68)	(-1.58)	(-0.44)	(-0.47)	(-0.98)	(0.66)
TERM	-0.501**	-1.419***	-0.545	-0.243	-0.066	-0.066	-0.265	-0.903**
	(-2.48)	(-3.88)	(-0.75)	(-0.75)	(-0.28)	(-0.18)	(-0.97)	(-2.52)
CREDIT	-1.881***	-4.407***	-0.387	-2.518***	-0.518	-0.997	-1.848***	-2.491***
	(-6.74)	(-5.81)	(-0.40)	(-5.45)	(-1.36)	(-1.36)	(-3.75)	(-4.58)
UMD	0.031**	-0.026	0.035	0.009	0.042***	0.051***	0.032***	0.073***
	(3.35)	(-1.51)	(1.16)	(0.71)	(4.93)	(3.51)	(2.77)	(4.84)
LIQ	0.001	0.032	-0.086**	0.014	-0.002	0.018	0.013	0.021
	(0.12)	(1.24)	(-2.11)	(0.94)	(-0.17)	(0.87)	(0.87)	(1.07)
Obs	239	239	239	239	239	239	239	239
R-squared	0.164	0.480	0.601	0.698	0.259	0.809	0.590	0.589

Table VIII

Relation between Fund Information Skill (FIS) and Performance

The table reports monthly returns of 10 equal-weighted portfolios of hedge funds sorted on their fund information skill (FIS), which is the covariance of a hedge fund's returns with the $INFO$ factor. In each month for each hedge fund with at least 18 returns observations in the past 24 months, a fund's FIS is estimated by regressing the fund excess returns on $INFO$ controlling for the market factor (MKT). Based on the funds' FIS, we form 10 equal-weighted portfolios. For each portfolio, alpha is estimated based on the monthly time series of the portfolio returns, relative to the Fung and Hsieh (2004) seven-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Both monthly excess return and alpha are reported in percentages, with t-statistics reported in the next column.

Deciles	*Fund FIS*	*Excess Return*	*t-stat*	*Alpha*	*t-stat*
1 (Low)	-0.312	0.267	1.72	0.008	0.85
2	-0.111	0.344	2.65	0.185	2.59
3	-0.050	0.300	2.56	0.176	2.82
4	-0.014	0.293	2.76	0.170	2.84
5	0.012	0.296	2.77	0.174	2.82
6	0.037	0.309	2.78	0.173	2.71
7	0.064	0.345	2.97	0.195	2.93
8	0.102	0.360	2.76	0.219	3.11
9	0.167	0.447	3.03	0.266	3.20
10 (High)	0.365	0.587	3.20	0.322	2.81
High minus Low	0.677	0.319	2.56	0.314	3.01

Table IX

***INFO* Factor and Hedge Fund Returns within Different Investment Styles**

For hedge funds in each investment style, we sort hedge funds into deciles based on their fund information skill (FIS), which is the covariance of a hedge fund's returns with the $INFO$ factor. In each month for each hedge fund with at least 18 returns observations in the past 24 months, a fund's FIS is estimated by regressing the fund excess returns on $INFO$ controlling for the market factor (MKT). The directional hedge funds include the funds with the investment style of long/short equity and dedicated short bias. The nondirectional hedge funds include the funds with the investment style of convertible arbitrage, event driven, and equity market neutral. Alpha is estimated relative to the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Both monthly excess return and alpha are reported in percentages, with associated t-statistics shown below in parentheses.

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
					Panel A: Directional hedge funds						
FIS	-0.387	-0.173	-0.093	-0.038	0.007	0.050	0.097	0.154	0.242	0.460	0.847
Ret	0.209	0.341	0.387	0.309	0.340	0.382	0.422	0.464	0.550	0.654	0.445
t-stat	(1.48)	(2.07)	(2.22)	(1.91)	(2.15)	(2.47)	(2.47)	(2.55)	(2.64)	(2.71)	(3.11)
Alpha	0.041	0.212	0.222	0.165	0.230	0.239	0.266	0.303	0.385	0.475	0.434
t-stat	(0.34)	(1.87)	(2.44)	(2.01)	(2.70)	(3.25)	(3.36)	(3.26)	(3.08)	(2.95)	(2.90)
					Panel B: Multi-strategy hedge funds						
FIS	-0.371	-0.136	-0.056	-0.018	0.009	0.039	0.071	0.111	0.172	0.347	0.718
Ret	0.313	0.437	0.571	0.423	0.370	0.442	0.323	0.388	0.515	0.704	0.391
t-stat	(1.87)	(3.01)	(4.33)	(3.09)	(2.87)	(2.89)	(2.41)	(2.10)	(3.33)	(3.45)	(1.89)
Alpha	0.220	0.385	0.492	0.335	0.339	0.382	0.230	0.337	0.427	0.623	0.403
t-stat	(1.09)	(3.62)	(4.93)	(3.33)	(3.47)	(3.38)	(2.60)	(2.79)	(3.50)	(3.77)	(2.11)
					Panel C: Nondirectional hedge funds						
FIS	-0.200	-0.058	-0.022	0.000	0.017	0.034	0.052	0.074	0.110	0.232	0.431
Ret	0.475	0.427	0.340	0.354	0.292	0.359	0.289	0.310	0.413	0.384	-0.091
t-stat	(3.50)	(3.76)	(3.34)	(3.53)	(2.42)	(3.06)	(2.23)	(2.09)	(2.65)	(1.96)	(-0.58)
Alpha	0.402	0.337	0.241	0.294	0.223	0.283	0.219	0.256	0.331	0.289	-0.113
t-stat	(3.57)	(4.15)	(3.62)	(4.81)	(3.01)	(4.15)	(2.96)	(2.75)	(3.46)	(2.28)	(-0.53)
					Panel D: Funds of funds						
FIS	-0.239	-0.099	-0.054	-0.023	0.003	0.029	0.059	0.093	0.148	0.300	0.540
Ret	0.128	0.177	0.261	0.249	0.263	0.277	0.327	0.325	0.329	0.411	0.283
t-stat	(0.19)	(1.44)	(1.94)	(1.86)	(2.13)	(2.15)	(2.52)	(2.33)	(2.10)	(2.36)	(1.53)
Alpha	-0.010	0.089	0.174	0.156	0.174	0.188	0.228	0.232	0.217	0.284	0.294
t-stat	-(0.07)	(1.24)	(1.95)	(1.89)	(2.31)	(2.44)	(2.98)	(2.68)	(2.20)	(2.15)	(1.67)

Table X
Value-Weighted Measure of *INFO* Factor

Panel A reports summary statistics for the value-weighted information factor ($INFO_VW$), the market factor (MKT), the momentum factor (UMD), the size factor (SMB), the value factor (HML), the profitability factor (RMW) and the the investment factor (CMA), the HXZ (2015) size factor (ME), the HXZ (2015) investment factor (IA), and the HXZ (2015) ROA factor (ROA) We first construct an information score for each stock in each month based on the informed trading of firm insiders, short sellers, and option traders. Specifically, for each measure of informed trading, we assign a rank (from 1 to 100) to each stock, where a higher rank is assigned to the value of the informed trading variable associated with a level of positive private information. A stock's information score is the arithmetic average of its ranking percentile for each of the three information trading variables.The $INFO\_VW$ factor is the value-weighted return spread between the decile of stocks with the highest information score and the decile of stocks with the lowest information score. Panel B reports summary statistics for long- and short-leg of the $INFO_VW$ factor. For each factor, we report the mean (in percent), standard deviation (in percent), Sharpe ratio, minimum return (in percent), skewness, and kurtosis for the entire sample period from February 1986 to December 2015.

Panel A: Raw Return of Value-Weighted INFO_VW

Factor	Mean	Standard Deviation	Sharpe Ratio
INFO_VW	1.252	4.713	0.225

Panel B: Alpha of INFO_VW Factor

	FF3+LIQ factors	FF5 factors	HXZ q-factors
	(1)	(2)	(3)
Alpha	1.277***	1.135***	1.287***
	(3.76)	(3.26)	(3.66)
Obs.	239	239	239
Adj. R-squared	0.012	0.027	0.015