DISCUSSION PAPER SERIES

No. 10471

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FINANCIAL ECONOMICS

Centre for Economic Policy Research

ISSN 0265-8003

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Discussion Paper No. 10471
March 2015
Submitted 19 February 2015

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Abstract

The existing literature treats the short side (i.e., short selling) and long side of hedge fund trading (i.e., changes in holdings) independently. The two sides, however, complement each other in revealing important economic motivations of trading: opposite changes in short interest and hedge fund holdings are likely to be driven by information, whereas simultaneous increases (decreases) in short interest and hedge fund holdings may be motivated by hedging (unwinding) considerations. We use this intuition to identify informed demand, and document that it exhibits highly significant predictive power on returns: stocks with informed long demand can outperform stocks with informed short demand by approximately 10% per year. We also find that informed demand forecasts future firm fundamentals (e.g., ROA, earnings surprise, analyst revision) but that it is less related to mutual fund flows or liquidity provision. These findings suggest that information discovery about firm fundamentals could be among the most important drivers for informed demand.

JEL Classification: g23
Keywords: short-selling

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Introduction

Hedge funds are known to both buy and short sell stocks on a large scale. Changes in hedge fund holdings and fluctuations in short interest are therefore two facets of the same phenomenon: hedge fund trading. The literature, however, treats these two variables separately, as if they were independent phenomena. For instance, the short selling literature investigates whether short sellers are informed and whether they can help improve price efficiency (e.g., Senchack and Starks, 1993, Asquith and Meulbroek, 1995, Aitken et al., 1998, Cohen, Diether, and Malloy, 2007, Boehmer, Jones, and Zhang, 2008, Boehmer and Wu, 2013, Karpoff and Lou 2010, Saffi and Sigurdsson, 2011, Hirshleifer, Teoh, and Yu, 2011, Akbas et al., 2013). The question of whether managers are informed and whether they can deliver superior performance is also at the core of the analysis of the hedge fund industry (Fung and Hsieh 1997, Ackermann, McEnally, and Ravenscraft 1999, Agarwal and Naik 2004, Getmansky, Lo, and Makarov 2004, Agarwal, Daniel, and Naik 2009, 2011, and Aragon and Nanda 2012).

However, a *joint* consideration of changes in both holdings and short interest has been lacking in the literature. This inattention is surprising because a joint approach would provide unique insights. Consider, for instance, the case in which the aggregate hedge fund ownership increases for a specific stock. While such a "net buy" may be driven by private information that predicts an increase in the stock price, it may also arise because of hedging – e.g., hedge fund managers use the long position to hedge out the systematic risk of their arbitrage strategy. It is not surprising, therefore, that changes in hedge fund ownership have not been found informative *ex ante* (e.g., Griffin and Xu, 2009), which may be simply due to the prevailing of the second effect (hedging). Indeed, in the presence of both trading motivations— i.e., hedging and information-driven— it is very difficult to properly assess the informational nature of hedge fund trading by just focusing on either long or short trades.

In this paper, we bridge this gap by proposing a novel approach that *jointly* considers short selling and hedge fund holdings to differentiate various types of trading motivations. Within the previous example, if

short interest decreases over the *same* period in which the aggregate hedge fund ownership increases, hedge funds as a whole are likely to trade on a positive signal, which we refer to as *informed long demand*. When the opposite pattern of trading occurs, in which case short interest increases over the *same* period when hedge fund ownership decreases, the trading reflects *informed short demand*. By contrast, a simultaneous increase (decrease) in both short interest and hedge fund ownership may occur when hedge funds use both the long and the short sides to form arbitrage portfolios (or to unwind existing arbitrate positions), which we can loosely define as *hedging* (*unwinding*) demand.[1] Given that in the case of *hedging* and *unwinding* demands, we cannot identify *ex ante* the direction of the signal of the hedge funds, if any, it is critical to net them out to properly identify the information dimension of hedge fund trading.

This novel identification strategy allows us to shed new light on the informativeness of hedge fund trading exploiting both hedge fund 13F filings and short selling information for the complete list of U.S. stocks for the period from 2000 to 2012. We proceed in three steps. In the first step, we rely on the traditional Fama-MacBeth specifications to detect the predictive power of informed demand for out-of-sample abnormal returns. For this purpose, we construct variables that proxy for *informed long demand* and *informed short demand* and use them to predict out-of-sample abnormal stock returns.

We find strong evidence that informed long (short) demand is associated with positive (negative) out-of-sample abnormal stock returns, suggesting that such demand is indeed informative. The economic magnitude is also highly significant. If we define informed long (short) demand as a dummy variable that takes the value of one when changes in short interests and hedge fund holdings belong to the most positive (negative) quartiles of stocks in the same period, we find that this proxy is related to a 6.6% (-3.2%) annualized abnormal return in the next quarter. In other words, stocks with informed long demand outperform stocks with informed short demand by as much as 9.8% per year. Similarly, if we directly

[1] Alternatively, one can also view the long-side and short-side of trading as coming from two different groups of traders, and interpret the *hedging* demand as the situation in which the two groups have different opinions regarding expected stock returns. The interpretation on informed demand, however, remains the same.

construct portfolios rebalanced at quarterly frequency that buy/sell stocks with informed long/short demand, the abnormal return over the entire sample period is approximately 10.5% per year. [2]

In the second step, we investigate the potential economic channels through which informed demand achieves its predictive power. For this purpose, we first split the sample into two subgroups based on a list of firm characteristics, including market capitalization, turnover ratio, analyst coverage, and dispersion of analyst forecasts. We then perform the return predictability test for each subsample of stocks. We find that return predictability is more significant for stocks with high market capitalization, a high turnover ratio, high analyst coverage, and high analyst dispersion. The association with the first three characteristics suggests that our findings are unlikely to be driven by (small) size related firm characteristics, (low) liquidity related market conditions, as well as (low) analyst coverage related public information, whereas the association with the last characteristic suggests that some sort of better information processing (e.g., Kim and Verrecchia 1994; Engelberg, Reed, and Ringgenberg 2012) could play a role in the predictive power of informed demand.

Motivated by this preliminary finding, we further explore the information content of informed demand by examining whether it can predict firm fundamentals, especially those unexpected by the market. Following Akbas et al. (2013), we consider various types of proxies for firm fundamentals. The first proxy is the real performance of firms—proxied by return on assets (ROA)—or changes in ROA, where ROA can be either adjusted or unadjusted by industry peers. The second type of proxy is related to the unexpected component of earnings, including standardized unexpected earnings (SUE). In addition to firm fundamentals, we also investigate whether informed demand can even predict analyst revision as well as the market response to unexpected firm-level fundamentals, where such a market response is proxied by the cumulative abnormal returns around earnings announcements (CARs).

[2] The results are robust to the use of different cutoff points for the definition of positive (negative) short interest and hedge fund holding changes, the use of different out-of-sample windows, and the inclusion of controls for hedging (unwinding) demand. In addition, placebo tests show that hedging and unwinding demands, unlike informed demand, do not exhibit consistent predictive power for returns, especially over the one-year horizon.

We find that informed demand has significant forecasting power for all the above measures, suggesting that the savvy traders behind such demand are not only well informed about firm-level financial information (ROA, SUE) but also sufficiently sophisticated to predict analyst revision and the market reaction to firm-level information.

Jointly, these results imply that the predictive power of informed demand may come from the discovery of information about firm fundamentals above and beyond what the market or even analysts know. Hence, return predictability documented in previous tests could be directly related to hedge fund managers' better information on the cash flows of companies. Overall, these findings support our intuition that the joint analysis of short selling and hedge fund holding changes is useful for revealing the trading motivations of perhaps the most sophisticated type of investors in the market.

In the last step of our analysis, we rule out a few alternative explanations of this return predictability. We first consider whether return predictability is related to a mechanical link between hedge fund strategies and mutual funds' flows. Indeed, hedge funds may trade to take advantage of the price impact of mutual fund inflows/outflows on stocks (e.g., Shive and Yun 2013; Arif, Ben-Rephael, and Lee 2014), which may lead to return predictability. However, we find that informed long (short) demand seems to be negatively (positively) correlated with mutual fund flows, which is the opposite of what a strategy of riding on the price impact of mutual fund flows would suggest.

Another potential alternative explanation is that return predictability may arise due to the risk premium associated with liquidity provision. Yet, we find that informed short demand is related to neither turnover nor Amihud liquidity measure. This finding, together with the previous finding that return predictability is more prominent for larger and more liquid stocks, suggests that the return predictability of hedge fund trading is unlikely to be related to liquidity provision.

Our paper is closely related to Griffin and Xu (2009). We extend Griffin and Xu (2009) by proposing that the use of information coming from short selling is necessary to identify informed demand shocks that are otherwise hidden among transactions with various motivations. To the best of our knowledge, we

are the first to propose such a joint analysis of short selling and hedge fund holdings and to link it to fundamental stock analysis. Our findings shed new lights on the informational content of both short sellers (Senchack and Starks, 1993, Asquith and Meulbroek, 1995, Aitken et al., 1998, Cohen, Diether, and Malloy, 2007, Boehmer, Jones, and Zhang, 2008, Boehmer and Wu, 2013, Saffi and Sigurdsson, 2011, Akbas et al., 2013) and hedge fund managers (Fung and Hsieh 1997, Ackermann, McEnally, and Ravenscraft 1999, Agarwal and Naik 2004, Getmansky, Lo, and Makarov 2004, Agarwal, Daniel, and Naik 2009, 2011, and Aragon and Nanda 2012).

The rest of the paper is organized as follows. Section II presents the data that we employ and the main variables that are constructed for the analysis. Section III presents the main empirical findings. Section IV performs robustness tests. Section V discusses the implications of the findings, and a brief conclusion follows.

II. Data and Construction of the Variables

The data that we use are compiled from various databases. We first retrieve hedge fund holding information from 13F filings from the Securities and Exchange Commission (SEC). Since 1978, institutional investors with at least a hundred million U.S. dollars under management are required to file 13F forms to the SEC each quarter for U.S. equity holdings of more than two hundred thousand dollars or more than ten thousand shares. This regulation allows us to construct holding or ownership data for each stock based on the aggregation of various types of institutional investors.

The identities of the hedge funds included in our sample are collected from the Thomson Reuters Institutional Holdings (13F) database, which are cross-referenced with 13F filings from the FactSet LionShares database. As noted by Ben-David et al. (2013), the hedge fund list identified in the Thomson Reuters 13F database is consistent with the FactSet LionShares identification of hedge fund companies. We identify hedge funds in the Thomson Reuters 13F database as follows. Institutional investors are divided into five types in this database: 1) bank trust departments, 2) insurance companies, 3) investment

companies and their managers, 4) independent investment advisers, and 5) others. We exclude institutions that are classified as type 1 or type 2.[3] For each remaining institution, we manually check its SEC ADV forms. Following Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we require an institution to have more than 50 percent of investment listed as "other pooled investment vehicles," including private investment companies, private equity, and hedge funds, or more than 50 percent of clients listed as "high net worth individuals" for inclusion in our hedge fund sample. We also require the institutions to charge performance-based fees to be included in the hedge fund sample. Finally, we manually check the website of each institution satisfying the above requirements to confirm whether its primary business is hedge fund-related activity.[4]

Although our sample can be extended to earlier periods, we focus on the post-2000 period because the number of hedge funds in 13F filings became reasonably large only toward the end of 1990s. Furthermore, the destabilizing effects of hedge funds on stock prices during the tech-bubble period of the late 1990s are well documented by Brunnermeier and Nagel (2004) and Griffin et al. (2011). We therefore need to avoid the confounding effects associated with the tech-bubble period.

In terms of stocks, we start with all the publicly listed companies for which we have accounting and stock market information from CRSP/Compustat. We then exclude ADRs and penny stocks (stocks priced at less than $1/share[5]) and stocks with incomplete information to construct control variables (as detailed below). Finally, we match the remaining stocks with the hedge fund holding data. Our final sample includes 5,357 stocks for the period from 2000 to 2012, invested by 1,397 hedge fund holding companies that report quarterly equity holdings in 13F filings.

[3] It is well-known that the type classification in the 13F database is inaccurate after 1998. However, the classification errors are almost entirely driven by misclassifying type 3 or 4 institutions as type 5 institutions (Lewellen, 2011); therefore, they do not affect our sample.

[4] Some of these institutions do not have websites. However, for most of them, we were able to identify whether they are hedge funds through a news search. The remaining institutions are included in the hedge fund sample because discussions with hedge fund managers indicate that some hedge funds are reluctant to maintain websites. Excluding these funds does not lead to qualitative changes in our results.

[5] See Ince and Porter (2006) for a more detailed discussion on these screening criteria.

Our main variables are constructed as follows. First, to construct our main dependent variable for the return predictability tests, we obtain the quarterly return, $r_{i,t}$, for stock i in a given quarter t as the compounded monthly returns as reported by CRSP. Following Daniel, Grinblatt, Titman, and Wermers (1997), we compute the abnormal performance of a stock, which we refer to as the DGTW-adjusted return, as the return of the stock net of the return of its style benchmark based on its size, book-to-market, and prior-period return characteristics.[6] We then compute the quarterly DGTW-adjusted return for each stock, denoted as $DGTW3_{i,t}$, as the compounded monthly DGTW-adjusted return of the stock in the quarter. We also compute the abnormal return over the one-year horizon in a similar way, which we denote as $DGTW12_{i,t}$.

Next, to construct our main independent variables, we compute short interest, $SI_{i,t}$, as the average monthly dollar value of short interest scaled by the total dollar value of all the outstanding shares of the stock in the month, both of which are obtained from Compustat. Because our hedge fund holding data are for each quarter-end, we use SI at the end of the quarter to extract quarterly changes in short interest. The use of the average short interest within a quarter leads to very similar results. Moreover, because our ultimate goal is to retrieve informed trading from both the long and the short sides of trading at the stock level, we also aggregate hedge fund holdings to compute hedge fund ownership for each stock, which we label $HFOwn_{i,t}$ for stock i in a given quarter t.

We define informed long demand as a dummy variable, $DLong_{i,t}$, which takes a value of one when hedge fund ownership increases from quarter $t-1$ to quarter t and when short interest decreases over the same period and takes a value of zero otherwise. That is,

$$DLong_{i,t} = I\{\Delta HFOwn_{i,t} > 0\} \times I\{\Delta SI_{i,t} < 0\},$$

where $I\{.\}$ is an indicator function, and $\Delta HFOwn_{i,t} = HFOwn_{i,t} - HFOwn_{i,t-1}$ and $\Delta SI_{i,t} = SI_{i,t} - SI_{i,t-1}$ denote the changes in hedge fund holdings and short interest, respectively.

[6] A detailed description and the data are available at http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/DGTW/coverpage.htm.

Similarly, informed short demand is defined as a dummy variable, $DShort_{i,t}$, which takes a value of one when hedge fund ownership decreases from quarter $t-1$ to quarter t and when short interest increases over the same period and takes a value of zero otherwise, i.e., $DShort_{i,t} = I\{\Delta HFOwn_{i,t} < 0\} \times I\{\Delta SI_{i,t} > 0\}$.

In addition to informed demand, we also define hedging and unwinding demand as a simultaneous increase and decrease in hedge fund ownership and short interest, denoted as $DHedge_{i,t} = I\{\Delta HFOwn_{i,t} > 0\} \times I\{\Delta SI_{i,t} > 0\}$ and $DUnwind_{i,t} = I\{\Delta HFOwn_{i,t} < 0\} \times I\{\Delta SI_{i,t} < 0\}$, respectively. Unwinding demand could be triggered by the need to liquidate existing trading positions to lock in profits or by fire sales. Although hedging demand and unwinding demand are interesting phenomena, a thorough examination of these phenomena is beyond the scope of this paper. Hence, we mainly focus on informed demand and provide only very preliminary analyses for these two variables—mainly as a Placebo test for the informed demand variables.

A second, alternative, way to define informed demand is to sort stocks into terciles according to $\Delta HFOwn_{i,t}$ or $\Delta SI_{i,t}$ and to then define informed long (short) demand as a dummy variable that takes a value of one if the stock's $\Delta HFOwn_{i,t}$ belongs to the top (bottom) tercile and if its $\Delta SI_{i,t}$ belongs to the bottom (top) tercile and that takes a value of zero otherwise. In other words, informed long demand, for instance, can be defined as the simultaneous occurrence of both the "highest" increase in hedge fund holdings and the highest decrease in short interest, where the "highest" increase or decrease is defined on the basis of tercile values of $\Delta HFOwn_{i,t}$ and $\Delta SI_{i,t}$ in a given period. To avoid confusion, we refer to tercile-based informed demand variables as $DLong_{i,t}^{Ter}$ and $DShort_{i,t}^{Ter}$. Similarly, we define informed short demand based on quartiles of $\Delta HFOwn_{i,t}$ and $\Delta SI_{i,t}$ values and denote them as $DLong_{i,t}^{Quar}$ and $DShort_{i,t}^{Quar}$, respectively.

The use of tercile- or quartile-based proxies of informed demand or hedging demand is more capable to capture trading driven either by more profitable information or by stronger hedging motivations. In

contrast, the previous variables of $DLong_{i,t}$ and $DShort_{i,t}$ defined based on positive or negative changes in short interest and holdings are likely to be more representative—as more stocks are involved—yet less informative. In later analysis, therefore, we will mainly rely on $DLong_{i,t}$ and $DShort_{i,t}$ to establish our main results. We will then verify that these results are robust to alternative definitions of informed demand and use quintile-based partitions to illustrate the economic magnitude of return predictability.

We also construct a list of control variables as follows. *DIV* is the dividend yield calculated as dividends divided by market capitalization; *Age* is the number of months since the stock first appeared in CRSP; and *Price* refers to the stock price per share. *Turnover* is the average stock turnover rate (volume divided by shares outstanding) over the past three months. *Vol* is the standard deviation of returns over the past 24 months. Finally, *SP500* is a dummy equal to 1 for stocks in the S&P 500 index and 0 otherwise. As indicated in the tables, we use natural log transformations of several of these variables in the regressions to reduce the impact of outliers.

Table 1 reports the summary statistics for our main variables. Our main proxies for informed demand, $DLong$ and $DShort$, have an average value of approximately 25%, suggesting that informed long and short demand occur approximately 25% of the time. Next, the average abnormal quarterly return is approximately 0.44%, with a standard deviation of 23%. This distribution is similar to what is reported in the literature.

Panel B of Table 1 presents the correlation coefficients of these variables. The most interesting pattern is that abnormal returns are positively associated with informed long demand and are negatively associated with informed short demand. This observation provides some initial support that informed demand could be related to stock returns. Of course, this pattern provides only preliminary and in-sample evidence of such a relation. In the next section, we move on to the out-of-sample return predictability of informed demand.

III. Return Predictability

In this section, we explore whether informed long or short demand can predict out-of-sample abnormal returns. We mainly rely on a multivariate specification, and we provide a portfolio-based analysis to verify the robustness of our findings.

A. Baseline Specifications

We estimate the following baseline Fama-MacBech regression at a quarterly frequency to detect the return predictability of informed demand:

$$DGTW_{i,t+1} = \alpha_i + \beta_i \times Informed\ Demand_{i,t} + C \times M_{i,t} + \epsilon_{i,t+1}, \qquad (1)$$

where $DGTW_{i,t+1}$ refers to the out-of-sample DGTW-adjusted abnormal return of stock i accumulated over quarter $t+1$; $Informed\ Demand_{i,t}$ refers to a vector of informed demand variables, including $DLong_{i,t}$ and $DShort_{i,t}$ in the lagged quarter; and $M_{i,t}$ stacks a list of control variables, including *DIV*, *LgAge*, *LgPrice*, *LgTurn*, *LgVol*, and *SP500*.[7]

The results are reported in Table 2. In Panel A, Models (1) to (3) provide the results of the baseline regression on the quarterly return predictability of $DLong_{i,t}$ and $DShort_{i,t}$. We find that, independently or jointly, $DLong_{i,t}$ forecasts positive abnormal returns and that $DShort_{i,t}$ forecasts negative abnormal returns in the next quarter. The predictive power is highly statistically significant, which is consistent with the idea that these two variables capture the informed demand of hedge fund managers/short sellers.

While this paper focuses on informed demand, Models (4) to (6) nonetheless provide a preliminary analysis of the impact of hedging demand and unwinding demand ($DHedging_{i,t}$ and $DUnwind_{i,t}$). We find that hedging demand is typically associated with positive abnormal returns and that unwinding demand is typically associated with negative abnormal returns. However, the return predictability of hedging demand is not as robust as that of informed demand. To illustrate this point, we report the return

[7] Because the dependent variable already nets out the size, book-to-market, and momentum characteristics for similar stocks, we do not explicitly include these three characteristics in the current regression. Adding these additional control variables does not affect our results.

predictability for tercile-based (in Model 7) and quartile-based (in Model 8) informed and hedging demand. As mentioned above, demand variables that are defined in this way represent more profitable information or more extreme hedging motivations than are typical for hedge funds. From these two models, although (more profitable) informed demand still forecasts abnormal returns, the predictive power of (more extreme) hedging and unwinding demands becomes marginal, if not insignificant. This result confirms the scarce informational content of hedging demand.

Panel B provides further insights by relating informed, hedging, and unwinding demands to the cumulative abnormal returns over the next 12-month period. We see that informed long (short) demand still predicts positive (negative) abnormal returns over this longer forecasting period. The return predictability of hedging and unwinding demand, however, disappears completely, suggesting that the 3-month return predictability of hedging and unwinding demand may reflect only a short-term price impact that is diluted over the longer horizon of 12 months. By contrast, the return predictability of $DLong_{i,t}$ and $DShort_{i,t}$ remains significant over the 12-month horizon, suggesting that it is unlikely to be driven by a short-term price impact. Thus, hedging demand and unwinding demand provide a sort of Placebo test with respect the informativeness of $DLong_{i,t}$ and $DShort_{i,t}$.

The economic magnitude of the return predictability of $DLong_{i,t}$ and $DShort_{i,t}$ is also sizable. To provide an example, consider Model (8) of Panel A, in which the regression parameters for $DLong_{i,t}$ and $DShort_{i,t}$ are 0.016 and -0.008, respectively. Hence, informed long demand and short demand are generally associated with an annualized abnormal return of 6.6% (annualized as $(1 + 0.016)^4 - 1$) and -3.2% (annualized as $(1 - 0.008)^4 - 1$) in the following quarter, respectively. If we add the two parameters together, we find that stocks with informed long demand outperform stocks with informed short demand by as much as 9.8%. The corresponding return difference implied by Model (3) is 4.4%. Although smaller in magnitude, the economic impact is no less impressive given that the stocks that are covered by such long and short demand are approximately 25% of the stocks in a given period.

B. Portfolio Analysis

A better way to illustrate the economic magnitude is to construct portfolios based on our informed demand variables and then compute the long-term performance based on these portfolios. To implement such a strategy, we long (short) stocks that have substantial informed long (short) demand.

Model (1) in Table 3 provides the results for this empirical strategy. At the beginning of each quarter, we focus on stocks that have the highest informed long (short) demand on the basis of terciles of short interest and hedge fund ownership changes in Panel A and quartiles of short interest and hedge fund ownership changes in Panel B. We report the long-run abnormal return that can be generated by these stocks. The results show that stocks with informed long (short) demand generate significant positive (negative) abnormal returns in the long run and that the difference between these two groups of stocks is highly significant, both statistically and economically. For instance, stocks with quartile-based informed long demand can generate a quarterly DGTW-adjusted return of 2.12% in an equal-weighted portfolio, which translates into an annual return of 8.76%. These stocks outperform those with quartile-based informed short demand by 2.53% per quarter, or 10.5% per year. The magnitude is close to what we obtain from the multivariate analysis. Value-weighted portfolios yield consistent results.

In Models (2) to (4) of Table 3, we further explore how the return predictability of informed demand decays over time. To do so, we report the average out-of-sample abnormal return that can be generated over two, three, and four quarters after the quarter in which we construct informed demand. Models (2) to (4) report the cumulative DGTW-adjusted return over these longer holding periods. The most important finding is that performance does not reverse in the future: the cumulative return difference between equal-weighted long and short portfolios in Panel B, for instance, amounts to 4.54%, 5.25%, and 5.8% over the next two, three, and four quarters, respectively. The first quarter abnormal return is 2.53%, which decays to 2%, 0.7%, and 0.5% in the second, third, and fourth quarters, respectively. The decay in the abnormal return is not accompanied by a price reversal.

The evidence in Table 3, therefore, is generally consistent with a slow diffusion of information in the market. Of course, the type of information underlying this return predictability is unclear. To address this issue, we will relate informed demand to various types of firm fundamentals.

IV. Informed Demand and Firm Fundamentals

Thus far, our results demonstrate that informed demand retrieved from the joint analysis of short selling and hedge fund holding information has significant forecasting power for out-of-sample stock returns. The next step is to investigate the channels through which informed demand obtains such predictive power. In this section, therefore, we explore the hypothesis that the source of return predictability for informed demand comes from informed investors' ability to forecast firm fundamentals.

A. Subsample Analysis

We start by splitting our sample into two subgroups based on a list of firm characteristics such as market capitalization, turnover ratio, analyst coverage, and dispersion of analyst forecasts. Splitting the sample into these subgroups allows us to better understand the effect of size and liquidity on return predictability. We therefore perform the return predictability tests as in Model (3) of Table 2 for each subsample of stocks.

Table 4 reports the corresponding regression results. More specifically, Models (1) and (2) apply the baseline specification to the subsamples of firms with small and large market capitalization on the basis of a 50%-50% split. We find that the return predictability of both long and short demand remains significant in the subsample of large firms but that short demand loses its predictive power in small firms. This pattern suggests that return predictability is unlikely to be driven by firm characteristics or stock returns related to (small) size, because otherwise we would find stronger return predictability for smaller stocks. To the contrary, our results may suggest that the stronger short sale constraint faced by small stocks may distort information discovery and dissemination.

Consistent with this intuition, Models (3) to (8), which tabulate the regression results for stocks with different turnover ratios, analyst coverage, and analyst dispersion, illustrate that the return predictability of both long and short demand remains significant mostly for stocks with high liquidity (i.e., high turnover ratios) and high analyst coverage/dispersion. The results on turnover suggest that the abnormal return predicted by informed demand is not merely a compensation for illiquidity-related market conditions. The findings regarding analyst coverage/dispersion suggests that $DLong_{i,t}$ and $DShort_{i,t}$ appear to be informed even in the presence of analysts, indicating that hedge fund managers are better able to process information than analysts (e.g., Kim and Verrecchia 1994; Engelberg, Reed, and Ringgenberg 2012).

B. Forecasting Firm Fundamentals

Our previous tests illustrate that the predicting power of informed demand does not stem from firm characteristics or market conditions related to (small) size, (low) liquidity, and (low) analyst attention. But what is such informed demand about? To answer this question, we now explore the extent to which informed traders can predict firm fundamentals. In the spirit of Akbas et al. (2013), we explore a few proxies of unexpected shocks in firm fundamentals. The first is related to the real performance of firms, proxied by return on assets (ROA) or changes in ROA, adjusted or unadjusted by industry peers. We calculate ROA by dividing the firm's income before extraordinary items by its total assets. Further, we define ΔROA as the difference between the ROA of the current quarter and the ROA from four quarters earlier (i.e., the same quarter in the previous year to account for seasonality in operating performance), and we define $Ind\text{-}adj\ ROA$ ($Ind\text{-}adj\ \Delta ROA$) as ROA minus its industry mean of the quarter, where industries are defined by the 2-digit SIC codes. We repeat the return predictability regression as specified in equation (1), but we replace the dependent variable out-of-sample abnormal returns with out-of-sample ROA in the 12-month period following the construction of informed demand.

The results are reported in Models (1) to (4) of Table 5. Across all these specifications, we find that $DLong_{i,t}$ and $DShort_{i,t}$ forecast positive and negative ROA of firms, respectively. The predictive power

is again highly significant, which is consistent with the notion that informed demand reflects capable traders' ability to forecast firm fundamentals.

Although ROA reflects the long-term profitability of firms, the financial market typically pays special attention to short-term cash flows such as earnings. Thus, another way to achieve return predictability may be based on the ability of capable investors to process earnings-related information better than the market. Hence, our second proxy for (unexpected changes in) firm fundamentals is related to the portion of earnings that are unpredicted by the market, namely, standardized unexpected earnings (*SUE*). If the informed demand predictability is truly driven by information, we expect it to forecast *SUE*. Following Bernard and Thomas (1990), we compute SUE as $SUE_{i,t} = \frac{E_{i,t} - E_{i,t-4} - c_{i,t}}{\sigma_{i,t}}$, where $E_{i,\ t}$ is the quarterly earnings (income before extraordinary items) of firm *i* in quarter *t* and $E_{i,\ t-4}$ is the earnings of quarter *t-4*. $c_{i,\ t}$ and $\sigma_{i,\ t}$ are the time-series mean and standard deviation, respectively, of ($E_{i,\ t} - E_{i,\ t-4}$) over the last 8 quarters, with a minimum of four quarters of data required for the observation to be valid. *Analyst revision* is the change in the consensus analyst earnings estimate, computed as the difference in mean estimates from the previous month divided by the stock price at the end of the previous month.

We also supplement *SUE* with another important variable that may help us understand the information ability of capable traders, namely, analyst revisions. If informed demand forecasts not only *SUE* but also analyst revisions, then capable investors behind the demand have the ability to process earnings-related information, and their information advantage would exceed that of analysts. Models (5) and (6) confirm this conjecture: both $DLong_{i,t}$ and $DShort_{i,t}$ exhibit the proper power in predicting positive and negative *SUE* and analyst revisions, respectively. The predicting power on analyst revision is especially interesting, as it confirms that informed demand identified in our paper could be motivated by information superior to that of professional analysts.

Finally, hedge fund managers may also be sufficiently sophisticated to predict the market reaction to firm-level information, which would allow them to benefit from their trading. To explore this channel, we

examine whether informed demand forecasts the cumulative abnormal returns (CARs) around earnings announcements. The dependent variable in this case is constructed as the market-adjusted returns upon the earnings announcement over the [-1, 1] window, where the market is defined as the value-weighted portfolio of NYSE/AMEX/NASDAQ stocks. We find strong evidence that informed long (short) demand peaks before positive (negative) CARs, confirming that the information-processing ability of the hedge funds allows them to benefit from market reactions.

Overall, the results presented in this section support the working hypothesis that informed demand identified by the joint analysis of short selling and hedge fund ownership changes predicts firm fundamentals above and beyond the ability of the general public. Particularly, the main reason that informed demand predicts returns seems to be that it represents the demand of investors who have information and who trade on fundamentals. To further confirm this intuition, we need to rule out other non-fundamental-related sources of information. We explore such alternative explanations in the next section.

V. Alternative Explanations

We now investigate whether the source of information that generates return predictability is related to other non-fundamental-related sources or reasons. We start by asking whether return predictability is related to information on "dumb money," i.e., the exploitation of mutual fund flows. More specifically, if hedge funds can buy/sell stocks that have large mutual fund inflows/outflows, they may profit from the price impact of the subsequent mutual fund trading that is induced by the inflows/outflows (e.g., Shive and Yun 2013; Arif, Ben-Rephael, and Lee 2014 provides evidence on the daily frequency). We therefore examine the relationship between mutual fund flows and informed demand.

We follow Shive and Yun (2013) and use the quarterly aggregate mutual fund holding changes (scaled by trading volume) to proxy for the flows of capital in and out of a stock. In Table 6, we examine whether the return predictability associated with informed demand as identified in our paper is related to

mutual fund flows. We first relate informed demand to changes in mutual fund holdings in Model (1) and find a negative relationship. That is, informed long (short) demand typically predicts negative (positive) mutual fund holding changes. This finding is not surprising. If mutual funds are generally less informed than hedge funds, hedge funds could lead informed trades and mutual funds may simply supply liquidity to these trades.

The more interesting question is whether informed demand can directly forecast and arbitrage the price impact generated by large and uninformed flows of mutual funds, such as those associated with fire sales (e.g., Coval and Stafford 2007). To do so, we relate informed demand to large inflows and outflows of mutual funds.[8] In Models (2) and (3), we focus on large inflows and outflows, i.e., the flows with a magnitude in the top 10% of the distribution in each period. In Models (4) and (5), we further examine extremely large flows that belong to the top 5% of the distribution. We find that at the 10% level, informed long (short) demand predicts negative (positive) extreme inflows and positive (negative) large outflows, which is the opposite of what a strategy of riding on the price impact of large flows would predict.[9]

Another possible explanation for the return predictability of informed demand is liquidity provision. If $DLong_{i,t}$ and $DShort_{i,t}$ are related to liquidity supply, i.e., stock purchases (sales) in the presence of selling (buying) pressure, these variables should be associated with a return premium that compensates for liquidity provision. To examine this potential explanation, we regress liquidity measured in different periods—concurrent, next quarter, and next year[10]—on $DLong_{i,t}$ and $DShort_{i,t}$. We use two different

[8] Unreported tests show that informed demand is unrelated to Frazzini and Lamont's (2008) measure of mutual fund flows, which is also consistent with our conclusion that the informed demand identified in this paper is not driven by mutual fund flows.

[9] Note that hedge funds may nonetheless use flow-based strategies. Our findings only suggest that mutual fund flows are not a major source of the return predictability of the *informed* demand identified in this paper. Indeed, unreported tests show that hedging and unwinding demands are positively and negatively associated with mutual fund inflows, respectively. Hence, consistent with the findings from Table 2, hedge funds may use arbitrage strategies to benefit from the temporary pricing impact of mutual fund flows. These results suggest that hedge funds may use different strategies to benefit from mutual fund flows and private information.

[10] All periods are considered with respect to the quarter in which informed demand is constructed.

proxies of liquidity, turnover, and the Amihud liquidity measure,[11] and we report the results in Table 7, Models (1) to (3) for the turnover ratio and Models (4) to (6) for the Amihud liquidity measure.

Models (1) to (3) show that informed long demand reduces concurrent and future liquidity, whereas informed short demand is unrelated to liquidity. The reduction in liquidity, if anything, suggests that informed long demand consumes liquidity rather than supplies liquidity to the market. For Models (4) to (6), we find that informed short demand is still unrelated to liquidity at any horizon but that informed long demand is marginally related to a reduction in liquidity in the concurrent period. Again, informed demand does not seem to supply liquidity to the market. Furthermore, because Amihud liquidity can also be interpreted as a price impact, informed short demand does not seem to even benefit from a price impact; this conclusion is consistent with our findings from Table 2.

Overall, these findings fail to support alternative interpretations of predictability that differ from the discovery of information about firm fundamentals.

Conclusion

We investigate the informational content of the joint use of the long and short sides of hedge fund trading. We propose that opposite changes in short interest and hedge fund holdings are likely driven by information, whereas simultaneous increases (decreases) in short interest and hedge fund holdings are likely motivated by hedging (unwinding) incentives. This intuition allows us to utilize short selling and hedge fund holding information to identify informed long and short demand.

Using this identification strategy, we show that informed demand changes have high predictive power for returns. Further, informed demand predicts out-of-sample firm fundamentals, such as ROA, earnings surprises, analyst revisions, and CARs. By contrast, informed demand does not seem to be driven by

[11] More specifically, liquidity is proxied by turnover, defined as the average stock turnover in the last three months, or the average Amihud liquidity measure over the last twelve months, where the Amihud liquidity measure in month *t* is the average daily ratio of the absolute stock return to the dollar trading volume within the month.

mutual fund flows or liquidity provision. These findings suggest that the observed return predictability of informed demand can be explained in terms of the discovery of information about firm fundamentals.

Our results also suggest that short selling and hedge fund holdings complement each other in revealing important trading motivations of informed fund managers. More research that integrates short selling and hedge funds could therefore be fruitful in providing insights into information dissemination and asset price formation in the market.

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Table 1: Summary Statistics

This table provides summary statistics for the main variables. Panel A reports the mean, median, standard deviation, and 10% and 90% quantile values for each variable. Panel B reports the correlation matrix for these variables.

Panel A: Summary Statistics					
	Mean	Std Dev	10%	Median	90%
DLong	0.2465	0.4310	0	0	1
DShort	0.2405	0.4274	0	0	1
DHedging	0.2640	0.4408	0	0	1
DUnwinding	0.2418	0.4282	0	0	1
DGTW 3m	0.0044	0.2342	-0.2216	-0.0072	0.2254
DGTW 12m	0.0146	0.5298	-0.4404	-0.0291	0.4591
Div	0.0161	0.0398	0	0	0.0427353
LgAge	234.71	198.89	53.00	171.00	480.00
LgPrc	25.93	40.64	3.58	19.20	51.99
LgTurn	0.1637	0.1536	0.0258368	0.1185697	0.3559267
LgVol	0.1277	0.0806	0.0553191	0.1105017	0.2167841
SP500	0.1586	0.3653	0	0	1

Panel B: Correlation Matrix												
	DLong	*DShort*	*DHedging*	*DUnwinding*	DGTW 3m	DGTW 12m	*Div*	*LgAge*	*LgPrc*	*LgTurn*	*LgVol*	*SP500*
DLong	1											
DShort	-0.3219	1										
	(0.0000)											
DHedging	-0.3426	-0.3371	1									
	(0.0000)	(0.0000)										
DUnwinding	-0.323	-0.3178	-0.3382	1								
	(0.0000)	(0.0000)	(0.0000)									
Ret3	0.0171	-0.015	0.0088	-0.0109	1							
	(0.0000)	(0.0000)	(0.0023)	(0.0002)								
Ret8	0.0179	-0.0154	0.0027	-0.0056	0.4649	1						
	(0.0000)	(0.0000)	(0.3547)	(0.0572)	(0.0000)							
Div	-0.0012	-0.0035	-0.003	0.0033	0.0053	0.0079	1					
	(0.6685)	(0.2216)	(0.2902)	(0.2467)	(0.0665)	(0.0075)						
LgAge	0.0162	0.0033	-0.0041	-0.0113	0.0038	0.0068	0.0846	1				
	(0.0000)	(0.2500)	(0.1572)	(0.0001)	(0.1834)	(0.0212)	(0.0000)					
LgPrc	0.0026	0.0041	0.0066	-0.0072	-0.0028	-0.0086	-0.0357	0.1599	1			
	(0.3585)	(0.1493)	(0.0225)	(0.0126)	(0.3337)	(0.0035)	(0.0000)	(0.0000)				
LgTurn	-0.0238	0.0107	-0.0173	0.0458	-0.015	-0.0104	-0.0276	-0.0219	0.0344	1		
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)			
LgVol	-0.0071	-0.0076	-0.0233	0.0371	0.0093	0.0193	-0.0618	-0.1987	-0.2103	0.2294	1	
	(0.0134)	(0.0080)	(0.0000)	(0.0000)	(0.0012)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
SP500	0.0249	0.0101	-0.014	-0.0134	0.0063	0.0091	0.0298	0.4418	0.1882	0.1038	-0.1851	1
	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0281)	(0.0020)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Table 2: Results of the Baseline Regression

Panel A reports the results of the following baseline Fama-MacBech regression at a quarterly frequency:

$$DGTW_{i,t+1} = \alpha_i + \beta_i \times Informed\ Demand_{i,t} + C \times M_{i,t} + \epsilon_{i,t+1},$$

where $DGTW_{i,t+1}$ refers to the out-of-sample DGTW-adjusted abnormal return of stock i accumulated over quarter $t+1$; $Informed\ Demand_{i,t}$ refers to a vector of informed demand variables, including $DLong_{i,t}$ and $DShort_{i,t}$ in the lagged quarter; and $M_{i,t}$ stacks a list of control variables, including *DIV*, *LgAge*, *LgPrice*, *LgTurn*, *LgVol*, and *SP500*. Panel B replaces the dependent variable with the out-of-sample DGTW-adjusted abnormal return of stock i accumulated over one year starting from quarter t. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively. The sample includes firm-semiannual observations over the 2000-2012 period.

Panel A: Out-of-sample quarterly abnormal return (DGTW-adjusted) regressed on partitioned dp variables								
	DLong by positive/negative changes in long/short positions						DLong by terciles	DLong by quintile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DLong	0.008***		0.006***				0.012***	0.016***
	(4.06)		(3.49)				(3.91)	(2.97)
DShort		-0.007***	-0.005***				-0.007**	-0.008**
		(-4.11)	(-3.47)				(-2.37)	(-2.31)
DHedging				0.005**		0.003*	0.005*	0.006
				(2.51)		(1.98)	(1.80)	(1.46)
DUnwinding					-0.005**	-0.004**	-0.005*	-0.007*
					(-2.56)	(-2.09)	(-1.98)	(-1.81)
Div	-0.017	-0.017	-0.017	-0.016	-0.017	-0.017	-0.016	-0.017
	(-0.40)	(-0.39)	(-0.40)	(-0.37)	(-0.41)	(-0.39)	(-0.37)	(-0.39)
LgAge	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(1.88)	(1.94)	(1.91)	(1.93)	(1.93)	(1.94)	(1.88)	(1.79)
LgPrc	-0.005*	-0.005*	-0.005*	-0.006*	-0.006*	-0.006*	-0.006*	-0.006*
	(-1.76)	(-1.78)	(-1.76)	(-1.83)	(-1.84)	(-1.86)	(-1.81)	(-1.82)
LgTurn	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.54)	(0.55)	(0.57)	(0.48)	(0.52)	(0.50)	(0.54)	(0.50)
LgVol	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(-1.02)	(-1.03)	(-1.03)	(-1.01)	(-1.01)	(-1.01)	(-1.03)	(-1.06)
SP500	0.004	0.005	0.004	0.005	0.004	0.005	0.004	0.005
	(1.30)	(1.33)	(1.29)	(1.40)	(1.32)	(1.37)	(1.20)	(1.29)
Constant	-0.003	0.000	-0.002	-0.003	0.000	-0.001	-0.002	-0.002
	(-0.18)	(0.01)	(-0.09)	(-0.15)	(0.01)	(-0.06)	(-0.11)	(-0.10)
Observations	121,216	121,216	121,216	121,216	121,216	121,216	121,216	121,216
R-square	0.022	0.022	0.023	0.022	0.022	0.023	0.024	0.024

Panel B: Out-of-sampleannual abnormal return (DGTW-adjusted) regressed on partitioned dp variables								
	dp defined by median values						dp by terciles	dp by quintiles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DLong	0.017***		0.013**				0.022***	0.029***
	(3.57)		(2.46)				(3.07)	(3.98)
DShort		-0.016***	-0.012***				-0.015**	-0.021**
		(-4.16)	(-2.73)				(-2.39)	(-2.09)
DHedging				0.009**		0.006*	0.010	0.011
				(2.36)		(1.93)	(1.19)	(1.03)
DUnwinding					-0.008	-0.005	-0.003	0.007
					(-1.47)	(-1.00)	(-0.51)	(0.85)
Div	-0.115	-0.115	-0.115	-0.116	-0.114	-0.115	-0.116	-0.115
	(-1.26)	(-1.27)	(-1.27)	(-1.29)	(-1.28)	(-1.29)	(-1.29)	(-1.28)
LgAge	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
	(2.59)	(2.65)	(2.63)	(2.65)	(2.61)	(2.64)	(2.59)	(2.62)
LgPrc	-0.034**	-0.034**	-0.033**	-0.034**	-0.034**	-0.034**	-0.034**	-0.034**
	(-2.46)	(-2.46)	(-2.45)	(-2.47)	(-2.46)	(-2.47)	(-2.44)	(-2.46)
LgTurn	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.003
	(0.51)	(0.52)	(0.53)	(0.48)	(0.53)	(0.51)	(0.49)	(0.42)
LgVol	-0.016	-0.016	-0.016	-0.016	-0.016	-0.016	-0.017	-0.017
	(-0.89)	(-0.90)	(-0.89)	(-0.89)	(-0.88)	(-0.88)	(-0.91)	(-0.91)
SP500	0.024**	0.024**	0.024**	0.025**	0.024**	0.024**	0.024**	0.025**
	(2.24)	(2.26)	(2.23)	(2.29)	(2.27)	(2.28)	(2.16)	(2.23)
Constant	0.025	0.032	0.029	0.026	0.033	0.030	0.027	0.024
	(0.54)	(0.69)	(0.62)	(0.57)	(0.68)	(0.63)	(0.59)	(0.52)
Observations	114,713	114,713	114,713	114,713	114,713	114,713	114,713	114,713
R-square	0.021	0.021	0.021	0.020	0.020	0.021	0.023	0.022

Table 3: Portfolio-based Analyses

In Panel A, we first independently double sort stocks into terciles based on hedge fund 13F holding changes and short interest changes. We then focus on two portfolios of stocks that have experienced the largest net-long and net-short demand shocks. We then report the annualized DGTW-adjusted return that can be generated by the two portfolios over the entire sample period (2000-2012).

Panel A: Cumulative DGTW return of Tercile Information-based Informed Demand								
	DGTW return of equally-weighted portfolio				DGTW return of value-weighted portfolio			
	t+1	*t+1 to t+2*	*t+1 to t+3*	*t+1 to t+4*	*t+1*	*t+1 to t+2*	*t+1 to t+3*	*t+1 to t+4*
Dlong=1 in t	1.750%	3.260%	3.776%	4.041%	1.319%	2.398%	3.100%	3.413%
Dshort=1 in t	-0.186%	-0.328%	-0.123%	-0.185%	-0.732%	-0.439%	0.320%	0.115%
Dlong-minus-Dshort	1.936%	3.588%	3.899%	4.226%	2.050%	2.836%	2.780%	3.298%
t-stat	(5.41)	(6.48)	(5.92)	(5.80)	(4.79)	(5.00)	(4.64)	(3.89)

Panel B: Cumulative DGTW return of Quartile Information-based Informed Demand								
	DGTW return of equally-weighted portfolio				DGTW return of value-weighted portfolio			
	t+1	*t+1 to t+2*	*t+1 to t+3*	*t+1 to t+4*	*t+1*	*t+1 to t+2*	*t+1 to t+3*	*t+1 to t+4*
Dlong=1 in t	2.122%	3.532%	4.249%	4.741%	1.729%	2.758%	3.100%	3.696%
Dshort=1 in t	-0.409%	-1.008%	-1.003%	-1.053%	-0.330%	-0.055%	0.414%	0.595%
Dlong-minus-Dshort	2.531%	4.540%	5.252%	5.795%	2.059%	2.813%	2.686%	3.101%
t-stat	(4.75)	(5.76)	(5.50)	(4.98)	(3.58)	(3.25)	(2.59)	(2.55)

Table 4: Subsample Analyses

This table applies the baseline regression from Table 2 to subsamples of stocks constructed based on different stock characteristics, including market capitalization, turnover ratio, analyst coverage, and dispersion of analyst forecasts. For each of the characteristics, we split the sample in any given quarter into two subsamples based on the median value. We then apply the baseline regression to each subsample of stocks and tabulate the regression results. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Panel A: Subsample analyses for out-of-sample quarterly abnormal return (DGTW-adjusted)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm Size		Turnover		Analyst Coverage		Disperion of Analysts	
	Small	large	Low	High	Low	High	Low	High
DLong	0.008***	0.005***	0.003	0.009***	0.006*	0.007***	0.011***	0.007***
	(2.71)	(2.69)	(1.25)	(3.88)	(1.98)	(3.36)	(3.47)	(2.76)
DShort	-0.004	-0.007***	-0.006**	-0.005***	-0.007**	-0.004**	-0.006	-0.005***
	(-1.02)	(-4.39)	(-2.13)	(-2.73)	(-2.35)	(-2.54)	(-1.58)	(-2.76)
Div	-0.016	0.020	0.036	-0.053	0.011	-0.079	-0.062	-0.025
	(-0.29)	(0.45)	(0.64)	(-0.97)	(0.20)	(-1.60)	(-0.70)	(-0.44)
LgAge	0.007***	-0.003	0.003**	0.000	0.006***	-0.001	0.001	-0.000
	(4.16)	(-1.50)	(2.10)	(0.23)	(4.38)	(-0.59)	(0.27)	(-0.14)
LgPrc	-0.008*	-0.004	-0.005*	-0.005	-0.005	-0.010**	-0.010***	-0.005
	(-1.80)	(-1.42)	(-1.77)	(-1.38)	(-1.54)	(-2.50)	(-2.70)	(-1.05)
LgTurn	-0.000	0.000	0.004*	-0.009*	-0.001	-0.000	0.001	0.000
	(-0.01)	(0.10)	(1.76)	(-1.95)	(-0.45)	(-0.09)	(0.21)	(0.00)
LgVol	-0.004	-0.008	0.000	-0.010	-0.005	-0.007	-0.005	-0.004
	(-0.73)	(-0.92)	(0.09)	(-1.44)	(-1.00)	(-0.88)	(-0.72)	(-0.51)
SP500	0.029**	0.004	0.003	0.003	0.009	0.005*	0.003	0.006
	(2.01)	(1.46)	(0.76)	(0.92)	(1.25)	(1.79)	(0.78)	(1.51)
Constant	-0.022	0.018	0.016	-0.022	-0.031	0.027	0.024	0.007
	(-1.06)	(0.88)	(0.84)	(-1.13)	(-1.54)	(1.43)	(1.15)	(0.34)
Observations	60,596	60,620	60,596	60,620	56,834	64,382	31,713	57,436
R-square	0.027	0.037	0.027	0.030	0.026	0.036	0.043	0.034

Panel B: Subsample analyses for out-of-sample annual abnormal return (DGTW-adjusted)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm Size		Turnover		Analyst Coverage		Disperion of Analysts	
	Small	large	Low	High	Low	High	Low	High
DLong	0.016	0.009**	0.010	0.017***	0.013	0.014***	0.011*	0.016***
	(1.45)	(2.52)	(0.87)	(3.46)	(1.13)	(3.80)	(1.88)	(3.58)
DShort	-0.012	-0.011***	-0.014*	-0.009*	-0.011	-0.012***	-0.008	-0.014**
	(-1.30)	(-3.72)	(-1.82)	(-1.92)	(-1.08)	(-2.93)	(-1.10)	(-2.39)
Div	-0.195	0.127	-0.061	-0.116	-0.067	-0.177	-0.209	-0.207
	(-1.59)	(1.23)	(-0.57)	(-0.76)	(-0.53)	(-1.46)	(-1.25)	(-1.51)
LgAge	0.030***	-0.006	0.013***	0.008	0.024***	0.002	0.008	0.007
	(6.11)	(-1.22)	(2.71)	(1.31)	(4.93)	(0.45)	(1.07)	(1.20)
LgPrc	-0.058***	-0.013	-0.031**	-0.035**	-0.038**	-0.038**	-0.036**	-0.032*
	(-2.92)	(-1.33)	(-2.51)	(-2.07)	(-2.60)	(-2.32)	(-2.40)	(-1.89)
LgTurn	0.004	-0.004	0.008	-0.013	-0.003	0.005	0.000	0.004
	(0.41)	(-0.63)	(1.08)	(-0.78)	(-0.41)	(0.43)	(0.03)	(0.26)
LgVol	-0.021	-0.008	0.000	-0.030	-0.016	-0.018	-0.015	-0.001
	(-1.40)	(-0.31)	(0.03)	(-1.29)	(-1.18)	(-0.79)	(-0.53)	(-0.05)
SP500	0.085**	0.015*	0.014	0.025**	0.011	0.022**	0.015	0.029**
	(2.30)	(1.95)	(1.10)	(2.44)	(0.44)	(2.64)	(1.67)	(2.65)
Constant	-0.037	0.069	0.063	-0.012	-0.061	0.097**	0.053	0.079*
	(-0.74)	(1.38)	(1.06)	(-0.21)	(-1.17)	(2.28)	(1.10)	(1.71)
Observations	56,068	58,645	56,895	57,818	52,759	61,954	30,325	55,085
R-square	0.027	0.037	0.026	0.032	0.025	0.035	0.041	0.031

Table 5: Forecasting Firm Fundamentals

This table explores the predictability of net demands on out-of-sample firm fundamentals. In Models (1) to (2), we regress firm ROA or changes in ROA in the following year on net long or short demand changes. Models (3) and (4) further adjust ROA or changes in ROA by the industry average. Models (5) and (6) tabulate the results for similar predictive regressions when the dependent variables are next-period SUE and analyst revisions. Model (7) reports the predictability of the net demand changes for next-period CARs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Out-of-sample ROA or Changes in ROA				SUE or analyst revision		Mkt response
Dependent variable =	ROA	ΔROA	Ind-adj ROA	Ind-adj ΔROA	SUE	Analyst Revision	CAR
DLong	0.001***	0.001**	0.001**	0.001**	0.015**	0.010***	0.001***
	(3.18)	(2.40)	(2.44)	(2.44)	(2.61)	(2.94)	(3.09)
DShort	-0.001**	-0.001***	-0.001*	-0.001**	-0.033***	-0.006*	-0.001**
	(-2.29)	(-2.72)	(-1.84)	(-2.41)	(-5.96)	(-1.95)	(-2.31)
BM	0.002***	0.002***	0.003***	0.001***	-0.006	-0.041**	0.001*
	(3.05)	(3.49)	(4.73)	(3.25)	(-0.64)	(-2.50)	(1.74)
Div	0.036***	0.002	0.028***	0.002	0.462***	-0.105	-0.019***
	(5.19)	(0.49)	(3.82)	(0.48)	(3.69)	(-1.57)	(-3.08)
LgAge	0.003***	0.001***	0.003***	0.001***	0.009*	0.002	0.000*
	(11.21)	(3.27)	(10.15)	(3.26)	(1.95)	(0.56)	(1.96)
LgPrc	0.016***	-0.001**	0.014***	-0.001**	-0.042***	-0.002	0.001**
	(14.82)	(-2.36)	(15.06)	(-2.14)	(-4.32)	(-0.52)	(2.52)
LgSize	0.000	0.001***	0.002***	0.001***	0.005	0.005*	-0.000
	(0.48)	(4.86)	(4.62)	(4.74)	(1.02)	(1.74)	(-0.92)
LgTurn	-0.000	-0.001***	-0.001***	-0.000**	-0.008*	-0.003	-0.001**
	(-1.03)	(-2.98)	(-3.52)	(-2.28)	(-1.74)	(-0.88)	(-2.43)
LgVol	-0.008***	-0.002**	-0.005***	-0.001**	-0.015	-0.017**	0.001*
	(-6.26)	(-2.02)	(-4.05)	(-2.14)	(-0.70)	(-2.42)	(1.74)
Ret3	0.011***	0.014***	0.010***	0.012***	0.227***	0.064***	-0.000
	(8.07)	(14.95)	(8.25)	(14.02)	(7.36)	(4.79)	(-0.18)
Ret8	0.007***	0.002**	0.006***	0.001	-0.114***	0.018***	-0.000
	(5.96)	(2.28)	(5.56)	(1.67)	(-5.79)	(3.19)	(-0.45)
SP500	-0.004***	-0.001**	-0.006***	-0.001**	0.000	0.002	-0.000
	(-5.47)	(-2.26)	(-8.84)	(-2.20)	(0.02)	(0.19)	(-0.24)
Constant	-0.098***	-0.027***	-0.095***	-0.024***	-0.173***	-0.221***	-0.001
	(-19.40)	(-6.00)	(-20.34)	(-5.96)	(-3.18)	(-8.64)	(-0.43)
Observations	111,513	111,040	111,513	111,040	110,949	95,336	105,846
R-square	0.188	0.032	0.165	0.028	0.039	0.015	0.020

Table 6: Informed Demand and Large Mutual Fund Flows

This table explores how informed demand reacts to mutual fund flows. In Model (1), we regress quarterly mutual fund holding changes ($\Delta MF\ Ownership$) on informed demand. Models (2) and (3) explore the relationship between informed demand and extreme mutual fund inflows and outflows, defined as flows within the top 10% of the distribution in terms of magnitude. Models (4) and (5) provide an alternative definition of extreme mutual fund flows, in which we use the top 5% of the distribution to define extreme flows.

	(1)	(2)	(3)	(4)	(5)
		Extreme Mutual fund flows (10%)		Extreme Mutual fund flows (5%)	
VARIABLES	ΔMF Ownership	Inflow	Outflow	Inflow	Outflow
DLong	-0.002***	-0.008***	0.012***	-0.003	0.007***
	(-4.09)	(-3.22)	(4.60)	(-1.63)	(3.78)
DShort	0.002***	0.011***	-0.007**	0.007***	-0.002
	(3.90)	(3.73)	(-2.39)	(4.52)	(-1.13)
BM	-0.000	0.012**	0.019***	0.010**	0.010**
	(-0.24)	(2.12)	(3.94)	(2.28)	(2.65)
Div	0.002	-0.133***	-0.099**	-0.060**	-0.077***
	(0.24)	(-3.69)	(-2.66)	(-2.29)	(-2.95)
LgAge	-0.000	-0.013***	-0.012***	-0.009***	-0.007***
	(-0.47)	(-8.40)	(-8.34)	(-7.78)	(-6.09)
LgPrc	0.001	0.023***	0.015***	0.016***	0.012***
	(1.19)	(7.68)	(5.01)	(7.74)	(6.26)
LgSize	0.001	-0.003	-0.005*	-0.002	-0.003**
	(1.11)	(-0.95)	(-1.81)	(-0.95)	(-2.39)
LgTurn	0.000	0.020***	0.023***	0.011***	0.015***
	(0.03)	(6.33)	(6.46)	(5.80)	(7.66)
LgVol	0.000	0.022***	0.023***	0.019***	0.018***
	(0.33)	(6.72)	(7.11)	(8.41)	(8.70)
Ret3	0.011***	0.029***	-0.053***	0.015**	-0.034***
	(6.68)	(4.25)	(-7.36)	(2.63)	(-6.49)
Ret8	0.004***	-0.003	-0.034***	-0.004	-0.023***
	(4.73)	(-0.76)	(-7.87)	(-1.11)	(-7.14)
SP500	-0.001	-0.039***	-0.034***	-0.026***	-0.024***
	(-0.74)	(-6.13)	(-6.45)	(-5.88)	(-8.20)
Constant	-0.017**	0.199***	0.346***	0.123***	0.211***
	(-2.05)	(14.22)	(22.17)	(10.44)	(20.16)
Observations	118,906	118,906	118,906	118,906	118,906
R-square	0.060	0.041	0.039	0.029	0.028

Table 7: Net Demand and Liquidity Provision

This table explores the relationship between liquidity and net demand changes. Models (1) to (3) regress the average turnover ratio of the firm in the concurrent period, the next quarter, and the next year with respect to the demand-change quarter, net demand changes, and a list of control variables. Models (4) to (6) replace the turnover ratio by the Amihud liquidity measure of the corresponding period.

	(1)	(2)	(3)	(4)	(5)	(6)
	y = Turnover Ratio			y = Amihud liquidity		
	Concurrent	Next Quarter	Next Year	Concurrent	Next Quarter	Next Year
DLong	-0.005***	-0.007***	-0.005***	-0.000*	-0.000	-0.000
	(-4.21)	(-5.62)	(-5.05)	(-2.00)	(-1.68)	(-1.50)
DShort	-0.001	-0.000	-0.002	-0.000	0.000	0.000
	(-0.31)	(-0.03)	(-1.23)	(-0.29)	(0.25)	(0.83)
BM	0.004***	0.003**	0.001	0.000	0.000	0.000**
	(3.68)	(2.24)	(0.91)	(0.21)	(0.92)	(2.09)
Div	0.055***	0.014	-0.028*	0.000	0.000	0.000
	(4.42)	(1.03)	(-1.98)	(0.89)	(0.39)	(0.86)
LgAge	-0.006***	-0.008***	-0.009***	-0.000	-0.000**	-0.000***
	(-7.51)	(-10.80)	(-14.51)	(-1.31)	(-2.25)	(-3.11)
LgPrc	0.020***	0.019***	0.018***	0.000***	0.000***	0.000***
	(12.05)	(8.76)	(8.09)	(6.77)	(6.59)	(7.43)
LgSize	-0.003***	-0.001	0.001**	-0.000***	-0.000***	-0.000***
	(-5.75)	(-0.95)	(2.19)	(-7.70)	(-8.14)	(-9.14)
LgTurn	0.094***	0.086***	0.081***	-0.000***	-0.000***	-0.000***
	(27.72)	(27.52)	(31.03)	(-7.07)	(-6.89)	(-7.66)
LgVol	0.065***	0.057***	0.051***	-0.000***	-0.000***	-0.000***
	(20.33)	(21.78)	(21.94)	(-2.78)	(-3.22)	(-4.02)
Ret3	0.023	0.040***	0.035***	-0.000*	-0.000***	-0.000***
	(1.57)	(3.71)	(5.24)	(-1.72)	(-2.82)	(-3.31)
Ret8	0.027***	0.017***	0.012***	-0.000	-0.000	-0.000
	(4.57)	(4.94)	(5.69)	(-1.37)	(-1.60)	(-0.87)
SP500	0.025***	0.019***	0.017***	0.000***	0.000***	0.000***
	(7.15)	(5.60)	(4.86)	(7.59)	(8.13)	(9.12)
Constant	0.454***	0.407***	0.388***	0.000***	0.000***	0.000***
	(22.49)	(21.99)	(27.73)	(7.18)	(7.59)	(10.14)
Observations	121,220	121,220	115,282	120,504	120,457	114,194
R-square	0.472	0.422	0.462	0.166	0.146	0.170