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Three Essays in Finance

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PREFACE

Chapter 1 of this dissertation titled “Permanent price impact asymmetry of trades with institutional constraints” with Chiraphol Chiyachantana, Pankaj Jain, and Christine Jiang is published at Journal of Financial Markets, volume 36, November 2017

Chapter 2 of this dissertation titled “Earnings expectations, forecasts, and the post earnings announcement drift” with Christine Jiang, and Emily Xu, is prepared for submission to Journal of Financial Economics.

Chapter 3 of this dissertation titled “Delayed disclosures and institutional trading” with Pankaj K. Jain, and Sandra Mortal, is prepared for submission at Economic Letters.

ABSTRACT

This dissertation research comprises three essays in finance. The first essay shows how dynamic institutional trading constraints related to capital, diversification, and short- selling asymmetrically affect the incorporation of new information as reflected in the Permanent price impact of their trades. The sign of the permanent price impact asymmetry between institutional buys versus sells is positive at the initial stage of a price run-up and reverses due to changing constraints with a prolonged price run-up in a stock. Idiosyncratic volatility, analyst forecast dispersion, trading intensity, price dispersion, and bullish market conditions further sharpen the initial asymmetry, as well as its reversal after a price run-up. The second essay we provide a new explanation for the post earnings announcement drift (PEAD). We hypothesize that the PEAD results from information production and the drift observed is a movement towards the changes in expectations and not an under-reaction or delayed response to the earnings announcement. We create a new measure that captures the changes in expectations over and above the earnings surprise. Our proxy is based on annual EPS forecasts by equity research analysts and takes into consideration both the responsiveness and the magnitude of the net changes in EPS forecasts. A long short trading strategy based on portfolios formed using our new measure generates higher returns compared to portfolios formed based on the earnings surprise measure. Most importantly, the earnings surprise based portfolio rankings loses its significance in explaining the PEAD when considered together with our new measure based portfolio ranking. In the third essay, we study trading by institutional investors around delayed disclosures. A disclosure is said to be delayed if there is a gap between the event date and the actual announcement of the event. We show that connected institutional trading can predict the information contained in these events, prior to it being disclosed.

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Chapter 1

Permanent price impact asymmetry of trades with institutional constraints

Abstract

Dynamic institutional trading constraints related to capital, diversification, and short-selling asymmetrically affect the incorporation of new information as reflected in the permanent price impact of their trades. The sign of the permanent price impact asymmetry between institutional buys versus sells is positive at the initial stage of a price run-up and reverses due to changing constraints with a prolonged price run-up in a stock. Idiosyncratic volatility, analyst forecast dispersion, trading intensity, price dispersion, and bullish market conditions further sharpen the initial asymmetry, as well as its reversal after a price run-up.

1. Introduction

The rapidly evolving literature on institutional trading has instigated a debate over the direction and cause of the asymmetry in the permanent price impact of institutional buys and institutional sells. The permanent price impact reflects the information content of institutional trades, which can be an indication of the quality of the institutions' research and their ability to exploit it profitably. As part of the price discovery process, new information about a stock's fundamentals gets impounded into the prices when investors trade. But the degree of the price impact is affected by the proportion of informed trading by institutions in the market, as not all institutions trade on their research and information due to various constraints.

Saar (2001) provides an intriguing theoretical model relating price history to asymmetric exploitation of information by institutions. The model challenges conventional wisdom about the positive sign of price impact asymmetry (higher price impact for institutional buys than for sells; see details in the literature review section) and describes the conditions under which the asymmetry can become negative. Normally institutions buy stocks with positive information and sell stocks when they have negative information. But they are not always able to implement trades because (a) institutions are reluctant to short sell when they do not initially hold the stock, which is true at the beginning of a price run-up associated with the initiation of buying activity;[1] (b) institutions are limited in their ability to borrow to invest, and thus face a capital constraint when buying at the later stages of a price run-up associated with the recent buying activity; and (c) institutions need to diversify their investments and are reluctant to add to positions in which they already have significant exposure from recent buying that creates the price run-up. Given these conditions, the Saar model shows that the history of stock price performance asymmetrically influences how

[1] Institutions, particularly mutual funds, are averse to short sales due to the possibility of unlimited losses on short positions, and regulatory constraints set forth by the SEC (Hong and Stein, 2003).

institutions trade to benefit from their information and analysis. Specifically, the asymmetry of the permanent price impact, defined as the permanent price impact of buys minus the permanent price impact of sells, starts out positive but diminishes with the increasing length of a price run-up. With an extended price run-up, institutional sells are likely unconstrained and share values are revised downward because of their trades. Thus, the asymmetry of price impact might even be negative if the price run-up history is long enough. Saar's model further identifies the determinants of the asymmetry in the permanent price impact including informational variables such as idiosyncratic volatility, analyst forecast dispersion, trading intensity, and stock price dispersion. To the best of our knowledge, the results of these theoretical predictions on permanent price impact have not been tested empirically. We fill this gap by empirically testing the leading theoretical model (Saar, 2001), which highlights the importance of stock price run-up history in gauging the information content of institutional trades under varying constraints.

Our paper further advances the literature on price impact asymmetry that has made much progress since the seminal study on block trading by Kraus and Stoll (1972). More recent works include Chiyachantana et al. (2004) who provides important insights on the impact of market condition on the price impact asymmetry. Using data for the London Stock Exchange, Bozcuk and Lasfer (2005) show the importance of the trade size and the ownership level that results from the trade. The large block trades are likely to convey private information and the level of institutional monitoring. Specifically, large buy (sell) trades that result in a significant increase (decrease) in post-trade ownership are likely to signal positive (negative) information and an increase (a reduction) in the degree of potential monitoring. Using Ancerno data, Anand et al. (2012, 2013) document significant differences in trading costs across institutions, and the importance of trading style for execution quality. Anand et al. (2013) propose a measure of an institution's trading style that captures the institution's propensity to trade in the direction of the daily return in the stock. They show that there is important heterogeneity in institutions' trading style and the implications of this heterogeneity in institutions' participation in the post-crisis recovery patterns.

We present new tests of price impact asymmetry and its determinants using a sample of institutions tracked by Ancerno, who collectively conducted 242 million trades worth $20 trillion during our sample period of 2001-2012. Our primary findings can be summarized as follows. Price impact asymmetry varies significantly based on the history of stock price run-up, informational variables, market conditions, and firm-specific characteristics. Asymmetry is positive for stocks that are at the initial stages of price run-ups, and turns negative when stocks have an extended period of run-ups. Moreover, the information content of institutional trades appears to be the strongest when institutions are buying at the initial stage of price run-ups or selling after a prolonged price run-up. These results point to constraints faced by institutions in their ability to trade on price-sensitive information or research. We also establish a link between institutional price impact asymmetry and variables that measure firms' information environment or information asymmetry. For stocks with a higher degree of information asymmetry, price impact asymmetry is higher for shorter price run-ups. Conversely, after a long price run-up, we see a larger reduction in asymmetry in price impact (from positive to negative) for these stocks with a higher degree of information asymmetry. Proxies for information asymmetry such as idiosyncratic volatility and analyst forecast dispersion are important determinants of price impact in the incremental sense after conditioning for liquidity characteristics and contemporaneous market condition. Our work relates to the relationship between institutional trading activity and stock prices. Our results show that institutional buys are not always more informative than sells. Instead, institutional constraints related to capital, diversification, and short selling affect the information content of institutional trades.

To ensure that our results are robust and our net permanent price impact (NPPI) measure reflects the pure effects of institutional trades devoid of the effects of risk and other systematic factors, we employ an experimental design where we have an institutional trading treatment group and a no institutional trade (NIT) control group. This approach also helps rule out the possibility that price patterns unrelated to institutional trades drive our results.

Our results should be of interest to a wide audience, as institutions currently hold 74% of stocks (Bogle, 2008), compared to 8% about 50 years ago. With a large fraction of aggregate wealth under their management, institutions are frequently the marginal price-setting agents in securities markets. Therefore, an investigation of their trading behavior and trading impact is necessary to understand the dynamics of stock prices. Our characterization of institutional trading practices, and in particular the information advantage of institutions and their ability to exploit it, represents an important step forward in assessing the value added by institutions under varying circumstances.

We organize the remainder of the paper as follows. Section 1 presents a discussion of the literature and the development of the hypotheses. In Section 2, we describe the data and our research design. We discuss our findings and robustness tests in Section 3and conclude in Section 4.

2. Literature review and research hypotheses

We begin with the definition of price impact commonly used in the literature, with emphasis on the permanent price impact. Institutions usually buy (sell) large quantities of a given stock and, in the process, move its price up (down). Following Kraus and Stoll (1972), total price impact is comprised of two parts: temporary price impact and permanent price impact. The temporary price impact relates to liquidity issues or widened bid-ask spread from a temporary imbalance in demand and supply; the temporary price impact disappears shortly after the completion of the trade. The permanent price impact represents any new information permanently impounded into the security price and the resulting price changes give rise to a new equilibrium price level that sustains well after the institutional trade is completed. We calculate the permanent price impact as the difference of the price after the completion of an institutional trade and the price before the arrival of the institutional order. It measures the long-lasting impact of an institutional trade on the stock price, and reflects the dissemination of new information into prices through institutional trades. The focus of our study is on the permanent price impact asymmetry that relates to informational issues.

The conventional wisdom based on studies by Kraus and Stoll (1972), Holthausen, Leftwich, and Mayers (1987, 1990), Chan and Lakonishok (1993, 1995), Keim and Madhavan (1995, 1997), and Engel and Patton (2004), is that the information content of institutional buys is higher than that of institutional sells. These papers suggest that buys are more informative because the decision to buy one security out of the entire universe of available stocks is indicative of strongly positive private information resulting from research and analysis. In contrast, negative information may only be utilized for the subset of stocks already held by the institution. Short-sale constraints restrict institutions from freely acting on all of their pessimistic views. Moreover, when an institution already has a long position, liquidity needs can trigger a decision to sell.[2]

[2] Liquidity-based reasons could include fund outflows, stock return exceeding the target, or availability of a better investment opportunity.

There are relatively few exceptions to this conventional wisdom in the literature about institutional buys having a greater permanent price impact than sells. Studies reporting a greater price impact of sell orders than that of buy orders include Chiyachantana et al. (2004), Brennan et al. (2012), and Jondeau, Lahaye, and Rockinger (2015). Chiyachanta et al. find that institutional buys have a higher total price impact in bull markets, whereas sells have a higher total price impact in bear markets. Brennan et al. compute buy and sell liquidity lambdas (a proxy for total price impact) to find that sell lambdas are greater than the buy lambdas. Jondeau, Lahaye, and Rockinger (2015) study 12 large capitalization stocks traded on the Euronext-Paris Bourse and find that the price impact is largely symmetric but the asymmetry can reverse for relatively less liquid stocks with a large proportion of buyer-initiated trades. We extend this literature by focusing on permanent price impact and directly testing Saar's (2001) institutional constraints theory for the first time using his price-run-up framework.

Saar (2001) predicts that the sequence of trades, information asymmetry, and recent price history taken together with institutional portfolio constraints can explain the permanent price impact asymmetry, which reflects the asymmetry in information content of institutional trades. Although informed traders would ideally want to use all the information from their research, in practice they use only some of their information due to constraints. At the beginning of a price run-up, institutions asymmetrically use their information. Positive information is used promptly and pervasively by implementing purchases, whereas the use of negative information is restricted due to short selling constraints. Thus, buy orders are likely based on positive information about the stock, while selling activities are limited only to trades from institutions that happen to hold the stocks in their portfolios. This increases the proportion of informed buys in the overall buying activity. Therefore, price impact related to the information content is expected to be higher for buy orders than for sell orders, and asymmetry is positive in the early stages of a price run-up or for shorter run-ups.

As positive information is released through institutional trades, more buyers are expected to become interested in the stock. In sequential trading, this causes a sequential increase in price levels in response to buy orders at the beginning of a price run-up. However, after a few days of a price run-up, it is likely that the positive information is largely incorporated into the price. Even if the institutional research indicates more potential for appreciation, buyers will limit the use of this information due to investment capital constraint or diversification constraint. The probability of an informed buy order arrival diminishes at this stage, decreasing the proportion of informed buys in the overall buying activity. The delay in response to the information indicates that institutional buying after a long price run-up may simply be herding instead of possessing any original positive information. Thus, prices will increase only slowly in response to buy orders after an extended price run-up. At this point, institutional sell orders might signal that the target price has been reached. Informed institutions are no longer constrained by short-sale restrictions, because they have more likely than not already accumulated a long position in the stock. When there is an institutional sale after several days of a price run-up, the market learns not only the information in the sale, but also that the informed buying will stop. These patterns lead us to predict a higher price impact from sells relative to buys after a prolonged price run-up. In essence, the asymmetry of permanent price impact diminishes with the duration of a price run-up due to both information content decay and a switch in the types of binding institutional constraints. Specifically, we test the following hypothesis:

Hypothesis 1: The asymmetry in information content reflected in the permanent price impact asymmetry (difference) between institutional buys versus sells is positive for a shorter price *run-up. After a prolonged price run-up, the asymmetry in information content or the permanent price impact of buys and sells becomes less positive or even negative.*

Recognizing that the nature of information space varies across stocks, we analyze how the firm-specific characteristics affect the information content of institutional trades and eventually the price impact asymmetry. We divide Hypothesis 2 into two parts, in the first part we look at the measures, which are stock characteristics and in the second at measures that depend on trading in the market. Stocks with a lower degree of information asymmetry do not lend themselves easily to information-based trading. In contrast, stocks with a high degree of information asymmetry may offer institutions an opportunity to gain a substantial information advantage through research. The asymmetric price impact effects described in Hypothesis 1 will be more pronounced for stocks that have a higher degree of information asymmetry at the beginning of a price run-up, and the magnitude of the reduction in asymmetry should also be more pronounced for such stocks after a long price run-up.

The literature points us to two measures of the degree of information asymmetry for individual stocks: idiosyncratic risk, and analyst forecast dispersion. Dierkens (1991) and Moeller, Schlingemann, and Stultz (2007) suggest that idiosyncratic risk can serve as a good proxy for the level of information asymmetry. Sadka and Scherbina (2007) use analyst forecast dispersion as a measure of information asymmetry. Analyst disagreement generally increases with earnings uncertainty. Hence, information asymmetry between the market maker and investors who are potentially better informed about future earnings will likely increase with analyst disagreement. To sum up:

Hypothesis 2a: Institutional trades in stocks with a higher degree of information asymmetry generate a higher price impact asymmetry for a shorter price run-up, and a speedier reduction in asymmetry after a prolonged price run-up relative to trades in low information asymmetry stocks.

Next, we consider two additional informational variables suggested by Saar (2001): trading intensity and stock price dispersion. Dufour and Engle (2000) show that, for frequently traded stocks, the price impact of a trade is larger and converges to its full information value faster when subsequent trades are clustered in time (i.e., when the trading intensity is high). Thus, we seek to determine whether asymmetry and its reduction as described in Hypothesis 1 becomes more acute with an increase in trading intensity. Similarly, according to Saar (2001), higher volatility or price dispersion could potentially amplify the price impact patterns in Hypothesis 1, i.e. after a long price run-up, the reversal in the price impact asymmetry is quicker.

Hypothesis 2b: Higher institutional trading intensity or higher price dispersion generate a higher price impact asymmetry for a shorter price run-up and a speedier reduction in asymmetry after a prolonged price run-up.

We believe that informational variables where they be stock characteristics or market driven will influence the informational content in institutional trades and the manner in which it diffuses into prices, given the constraints. Hypothesis 2a and 2b set forth our priors.

3. Data sources and research design

3.1. Data

We obtain proprietary institutional trading data from the Ancerno Corporation (formerly, Abel Noser). Ancerno provides consulting and advisory services to close to 1,000 domestic institutional clients representing between eight to ten percent of institutional trading in the U.S. (Puckett and Yan, 2011) during our sample period.[3] The database contains information on institutional orders about stock symbols, order direction (buy or sell), order quantity, value-weighted average stock prices on and before order placement date, order release dates (from institutional clients to trading desks), price at the time of release, number of shares released, code number of broker(s) used to fill the order, transaction price, quantity of shares traded, execution date, and commissions charged by the broker. Institutions tracked in the Ancerno dataset collectively transacted over $20 trillion during our sample period of 2001-2012. We merge our dataset and the CRSP dataset to obtain the historic prices and returns of individual stocks surrounding the institutional order date so that we can classify the orders into various price run-up categories.[4] We also obtain the analysts' current-fiscal-year annual earnings per share forecasts from the I/B/E/S Summary History file.

3.2 Measures of permanent price impact

Due to the increase in the overall trading volume in the markets and in particular, in institutional order flow, several trades occur within a second. Thus, it has become difficult to study the price impact of individual trades in the traditional sense. In most of our data we observe both Buy and Sell orders for the same stock on the same day for multiple times by the same institutional client. In such a case, it is difficult to determine the direction of the price impact, let alone the asymmetry. Anand et al. (2012, 2013) adopt the idea of stitching Ancerno institutional trades into

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[3] Over time, the name of the data provider has changed. Earlier it was referred to as "Abel Noser" or "ANcerno." The data source is the same as that used by Puckett and Yan (2011) and Busse, Green, and Jegadeesh (2012).

[4] To maintain the integrity of the data and filter out possible errors, we eliminate observations with missing prices or order quantities. In addition, following the approach of Keim and Madhavan (1995, 1997) and Conrad, Johnson, and Wahal (2001), we exclude orders for stocks trading under $1.00.

an institutional ticket. Building upon this idea, we devise a new trade imbalance measure that considers all buy and sell trades on the same stock on a given day as well as the splitting of orders into small trades.

Our measure of price impact asymmetry considers all trades of all sizes. For a given day, each stock, i, traded by institutional investors is assigned a direction based on whether the institutional trading imbalance ($\sum_i Volume_{buy}$- $\sum_i Volume_{sell}$) is positive or negative respectively. Going forward we denote them as buy imbalance and sell imbalance. The permanent price impact is the change in the prices from the previous equilibrium to the new equilibrium price.

$$\textit{Raw Permanent Price Impact}, PPI_{t+n} = \left(\frac{P_{t+n}}{P_{t-1}} - 1\right) * 100 * Direction, \qquad (1)$$

where P_{t+n} is the closing price *n* days after the institutional trade and P_{t-1} is the closing price on the day before that institutional order is placed. To ensure that the change in prices are not due to bid-ask bounce, we use mid-quotes for all our analyses.

Direction is an indicator variable equal to +1 for buy institutional imbalance stock-days and −1 for sell institutional imbalance stock-days. Permanent price impact reflects the changes in beliefs about the value of a security due to any new information signaled by trades. Thus, a positive value for permanent price impact is also an indication that the trades are associated with a valuation update resulting from the trader's information advantage. Our measure is similar to those used in studies on order flow imbalance by Hendershott, Livdan, and Schürhoff (2015) and Levi and Zhang (2015).

Hu (2009) raises a concern that pre and post-trade measures of price impact are influenced by market movements that give rise to the asymmetry. In order to alleviate such concerns and to isolate the price impact related to new fundamental information about the stock and to standardize it across stocks with different risk characteristics, we define the market-adjusted and risk-adjusted permanent price impact ($PPI_{i,t+n}$) for a given stock i as follows:

$$Adjusted\ PPI_{t+n} \ = \left\{\left(\frac{P_{t+n}}{P_{t-1}} - 1\right) - Benchmark\ return\right\} * 100 * Direction. \qquad (2)$$

We decide to report results for n = 1, 5, or 10 days, respectively. The shorter 1-day observation period minimizes the impact of any extraneous events that can occur in the days following the trade. In contrast, the medium 5-day window and the longer 10-day window allow sufficient time for information dissemination. We compute benchmark returns in two alternative ways. For market return-adjusted PPI, the benchmark return is simply (MI_{t+n}/MI_{t-1} −1). For beta-adjusted PPI, the benchmark return is defined as β_i * (MI_{t+n}/MI_{t-1} −1), where β_i is estimated using returns in a rolling prior 5-year window, and MI_{t+n} and MI_{t-1} are CRSP value-weighted index levels on dates t+n and t-1, respectively.

3.3 Formation of a control group to account for price patterns unrelated to institutional trades

We calculate price impact for various price history groups. We recognize that past returns and reversals may contribute to a large portion of price impact asymmetry relative to the portion contributed by institutional trades. To rule out this possibility, we adopt a modified price impact measure. For every trading day, we form a control group consisting of stocks not traded by institutions on that day, and the treatment group contains the stocks in our sample that were traded by institutions. We further divide the two groups into price run-up groups based on their prior price patterns. The difference between the two enables us to capture the pure price impact of institutional trades that only impacts the treatment group, net of the effects of price patterns such as reversals that will impact both the groups.

We now elaborate on the specific steps involved in computing the modified price impact measure. We begin by taking all stocks (share code 10 and 11) in the CRSP database. The control sample is formed each day to include the stocks that were not traded on that given day by institutions. Both the sample and the treatment stocks are assigned to their respective price run-up groups based on their price history (see detailed discussion in subsection 2.5). We then compute the price impact for both groups in these price run-up categories. The price change for the control group is computed in a manner similar to that of the benchmark PPI for treatment stocks. Note that the market adjustment drops out when we take the difference between the groups because the market adjustment is the same quantity for both groups. The NIT (no institutional trade) adjusted price impact (NPPI) is thus defined as:

$$\textit{NIT-adjusted PPI } (NPPI_{t+n}) = \text{Treatment } PPI_{t+n} - \textit{Control } PPI_{t+n}. \tag{3}$$

3.4. Trade size and permanent price impact

The price impact calculated for individual stock-days in the previous subsection must be aggregated and averaged within each price run-up group for further analysis. In this step, we want to rule out the possibility that any differences in the transaction sizes of buys and sells systematically affects our results. Thus, we calculate the net trade flow- weighted permanent price impact for each price history group g at t+n, $PPI(g)_{t+\mathrm{n}}$, as follows:

$$PPI(g)_{t+n} = \sum_{i=1}^{m} \frac{SV_i}{\sum_{i=1}^{m} SV_i} PPI_{t+n}. \tag{4}$$

Here SV_i is the net imbalance for a given stock i, and it is summed over all stock days in a given group. The weighting scheme is applied to raw *PPI*, market-adjusted *PPI*, beta-adjusted

PPI, and control group adjusted PPI (*NPPI*). Throughout the paper, we report this net imbalance weighted average permanent price impact.[5]

The price impact asymmetry (*PIA*) for each price group is defined as the difference between the permanent price impact of purchases and that of sells:

$$PIA\ (g)_{t+n} = PPI(g)_{t+n}^{Buy} - PPI(g)_{t+n}^{Sell}. \tag{5}$$

Price impact asymmetry is positive when the price impact of buys is greater than that of sells, and negative otherwise.

3.5 Defining price run-up and forming price run-up groups

Our analysis requires us to carefully define a price run-up as this is critical to our empirical design. Price run-up is defined as the number of days of consecutive positive market-adjusted returns in the stock just prior to the arrival of institutional orders. We search through the CRSP database to classify each calendar trading day into a price history group, which is based on the number of consecutive days that a stock experiences positive excess returns over the market before the trend stops or reverses. To rule out the possibility that different closing prices of a stock simply reflect bid-ask bounce, we use a stricter criterion, which requires the absolute return to exceed a transaction cost band of six cents, which approximately represents the average bid-ask spread in the post decimalization period and represents the tick size in the first few months of our sample. Thus, if the stock price on day *t* is within the six-cent range of the price on day *t*-1, we assume that

[5] In our robustness section, instead of using *SV* as weights, we use net dollar volume *(DV)* as weights to compute the dollar size-weighted price impact, average transaction volumes (*TV*) as weights to compute the trade size-weighted price impact, and 1/*m* as weights to compute the conventional equal-weighted price impact. Our results are not sensitive to the choice of weights.

there is no run-up on day *t* because the observed price change may merely be the bid-ask bounce. Excluding stock-days falling in the zero-return category, we have 2.87 million stock-days with price run-ups, as compared to 3.32 million stock days of price run-ups without the adjustment of transaction costs, a reduction of 16% in sample size.

We form three distinct price history groups: 1-day price run-up (+1), 2-5-day price run-ups (+2 to +5), and 6-10-day price run-ups (+6 to +10), respectively. The choice of +1, +2 to +5, and +6 to +10 is based on data distribution. The number of stock-days with more than 10 days of price run-up are too few to conduct any meaningful analysis. The longest price run-up days in our data is 18 days and only 1 stock day falls in that group. The percentage of the sample with price run-ups greater than 10 days is less than 0.04%, thus we decided to choose 10-day run-up as a reasonable cutoff. The choice of 1 and 2 to 5 is driven by creating two comparable sets of stock days, each exceeding 1 million observations (i.e., 1.7 million and 1.1 million, respectively). The choice of 6 to 10 in the remaining sample allows us to have a significant number of observations in the group, around 36,000, so that the categories are representative and meaningful.

4. Empirical results

4.1. Summary statistics

Table 1 provides the descriptive statistics for sample firms, explanatory variables, and control firms. We have 4,705 securities in our final sample, as noted in Panel A; their average market capitalization is \$3.15 billion, as shown in Panel C. The average volume-weighted trade price is \$32.62, and the average daily trading volume per stock is 3.95 million shares.

Our sample comprises 242 million institutional trades of all sizes. After aggregating stocks based on net institutional imbalances, we have 7.2 million stock-days. Of these, 2.87 million represent price run-up days and the rest are run-downs or no change. Each stock-day is categorized as having either net institutional buy imbalance or net institutional sell imbalance, based on whether the institutional trading imbalance ($\sum_i Volume_{buy}$- $\sum_i Volume_{sell}$) is positive or negative. Overall, there are 3.91 million stock-days that institutions have a buy imbalance, compared to 3.29 million stock-days with a sell imbalance. On a given day, we have an average of 801 stocks being traded in our sample that witnessed price run-ups.

We use two proxies of information asymmetry for each individual stock: idiosyncratic volatility and analyst forecast dispersion. We define idiosyncratic volatility as the standard deviation of the regression residual from the Fama-French three-factor model for each stock each month; its mean is 11.78%. The mean analyst forecast dispersion, defined as the standard deviation of analysts' current fiscal year annual earnings per share forecasts scaled by the share price, is 8.97%. Trading intensity, defined as a stock's total monthly trading volume divided by its total number of shares outstanding at the beginning of the year, averages at 2.02 times. Following Lee, Ready, and Seguin (1994), we calculate stock price dispersion as the percentage difference in the highest and the lowest closing prices in the 90 calendar days prior to an institutional order. Mean price dispersion is 37.81%. All the above variables are available at monthly frequencies. We calculate idiosyncratic volatility on a rolling window with the latest five years of data. The analyst forecast dispersion is calculated every month, with information of the most recent 12 months of forecasts, and the price dispersion is calculated monthly from price information of the most recent 90 days.

Panel C of Table 1 reports the stocks that form part of the control group. There are on average 692 stocks in the control group on a given day, with an average market capitalization of $2.23 billion. The volume-weighted stock price of the control group is $22.10, which implies that it is not comprised of low-priced, illiquid stocks and is comparable to that of the treatment group.

The market capitalization and daily trading volume are also close for the two groups. Hence, we believe that the *NIT*-adjusted measure of price impact will properly control for most market-wide changes and any short-term price trends unrelated to institutional trading. To further ensure that our groups are similar prior to institutional trading, we compare the pre-return performance of the control group with Ancerno stocks. In results reported in Panel D, we find that the pre-return cumulative abnormal returns (CAR) are similar for the two groups and the differences between the CARs for the two groups over prior 1-, 5- and 10-day windows is not significantly different at the 5% level.

Table 1. Summary Statistics

We report summary statistics for all institutional trades in the Ancerno dataset for the 2001 to 2012 period. Panel A provides an overview. Panel B has the summary of explanatory variables. *Idiosyncratic volatility* is estimated monthly, as mean squared errors from the regression of excess daily returns of each stock on the Fama-French three factors *Analyst forecast dispersion* is the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts divided by the absolute value of the mean forecast, as reported in the I/B/E/S Summary History file. *Trading intensity* is the monthly trading volume in a stock divided by the number of shares outstanding at the beginning of the year. *Price dispersion* is the percentage difference between the highest and the lowest trading prices in the 90 calendar days just prior to the institutional trade. Panels C and D show characteristics of institutional trades in Ancerno and the No Institutional Trade (*NIT*) Control group, which consists of stocks not traded by Ancerno institutions on a given day. We define price run-up history as the number of days of consecutive positive market adjusted returns in the stock prior to the arrival of the institutional trade. We calculate *t-statistics* using standard errors adjusted with the Newey-West (1987) procedure and reported in parentheses.

Panel A: Sample Characteristics	
Number of Securities	4,705
Total Number of Trades (million)	242
Total Number of Stock days (million)	7.20
Number of Stock Days with Buy Imbalance (million)	3.91
Number of Stock Days with Sell Imbalance (million)	3.29

Panel B: Summary Statistics of Explanatory variables

	Mean	Standard Deviation
Idiosyncratic Volatility (%)	11.78	5.34
Analyst Forecast Dispersion (%)	8.97	13.21
Trading Intensity	2.02	1.49
Price Dispersion (%)	37.81	27.16

Panel C: Ancerno Institutional Trading Sample and No Institutional Trade (NIT) Control Sample

	Ancerno Institutional	NIT Control
Average Securities Traded Every Day	801	692
Average Market Capitalization (billion $)	3.15	2.23
Volume Weighted Share Price ($)	32.62	22.10
Average Daily Volume (million)	3.95	2.08

Panel D: Pre-Return comparison of Ancerno and Control Sample

Price Run-Up History	*CAR (1 day prior)*			*CAR (5 days prior)*			*CAR (10 days prior)*		
	Ancerno	NIT	Diff.	Ancerno	NIT	Diff.	Ancerno	NIT	Diff.
1	-0.95	-1.11	0.16	-0.87	-0.84	-0.03	-0.67	-0.48	-0.20
			(1.44)			*(-0.42)*			*(-1.31)*
+2 to +5	-0.98	-1.18	0.19	-0.95	-0.98	0.03	-0.82	0.40	-1.21
			(1.27)			*(0.39)*			*(-1.26)*
+6 to +10	-0.95	-1.13	0.17	-1.14	-2.16	1.02	-1.14	-1.59	0.44
			(1.60)			*(1.73)*			*(0.46)*

4.2. Price impact asymmetry

Our measure of permanent price impact is based on institutional trading imbalance and captures the overall pressure that institutional investors exert on the market. Because our measure differs from prior studies, we first show that the results are consistent with those reported in the literature on price impact asymmetry. In Table 2, we report three different measures of permanent price impact for 1, 5, and 10 days after the trade date. We find that the permanent price impact asymmetry is positive for all three measures and the asymmetry increases as we move from 1 day to 10 days ahead. For the raw permanent price impact measured after 1 day of trades we find the asymmetry to be 0.18 bps, which increases to 1.25 bps for the permanent price impact asymmetry measured after 10 trading days. Our market-adjusted and risk-adjusted results are 0.14 bps and 0.08 bps for the 1-day price impact asymmetry, and 0.90 bps and 0.71 bps for the 10-day price impact asymmetry, respectively. Overall, our measure of *PPI* yields estimates that are consistent with what has been reported in the literature for example Keim and Madhavan (1996) and Kraus and Stoll (1972) report positive price impact asymmetry of around 0.10 %.

Table 2. Positive price impact asymmetry

We calculate the permanent price impact (PPI) of institutional trades, and the asymmetry in several ways.

Raw Permanent Price Impact of Institutional Trades, *PPI t*+*n*-= $\left(\frac{P_{t+n}}{P_{t-1}} - 1\right) * 100 * Direction$

Market Adjusted Permanent Price Impact of Institutional Trades, *MPPI t*+*n*=$\left\{\left(\frac{P_{t+n}}{P_{t-1}} - 1\right) - (\frac{M_{t+n}}{M_{t-1}} - 1)\right\} * 100 * Direction$

Beta Adjusted Permanent Price Impact of Institutional Trades, *BPPI t*+*n*= $\left\{\left(\frac{P_{t+n}}{P_{t-1}} - 1\right) - \beta * (\frac{M_{t+n}}{M_{t-1}} - 1)\right\} * 100 * Direction$. All stocks traded by institutions on a day are classified as having an institutional buy or sell imbalance based on whether the institutional trading imbalance ($\sum_i Volume_{buy}$- $\sum_i Volume_{sell}$) is positive (Direction=+1) or negative (Direction=-1) respectively. The subscript t denotes the trade date when the trade is executed; P_{t+n} and M_{t+n} denote prices on dates *t*+n and CRSP value weighted index levels on dates *t*+n respectively. We report results over three windows with values of *n* being 1, 5, and 10 days after the trade date. β is the rolling beta estimated from the Fama-French three-factor model using monthly return data over 5 years from CRSP. Price impact is averaged across stock days and weighted using the institutional imbalance. We define price impact asymmetry (*PIA*) as the difference between the permanent price impact of buy and that of sell. We divide the sample into three groups based on past price run-up of 1 day, 2-5 days, or 6-10 days. Price history is the number of days of consecutive positive market-adjusted returns or run-up prior to the institutional trading order. Price impact is averaged across orders within each group, and weighted by institutional trading imbalance. We calculate *t-statistics* using standard errors adjusted with the Newey-West (1987) procedure and reported in parentheses. The number of stock-day observations is 7,200,225

	PPI t+1			*PPI t*+5			*PPI t*+10		
	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry
PPI	0.78	0.60	0.18	1.02	0.23	0.78	1.28	0.03	1.25
			(2.70)			*(8.78)*			*(7.93)*
MPPI	0.79	0.64	0.14	0.94	0.39	0.55	1.11	0.21	0.90
			(2.18)			*(6.41)*			*(5.86)*
BPPI	0.77	0.69	0.08	0.88	0.43	0.45	0.98	0.27	0.71
			(1.29)			*(5.15)*			*(4.63)*

4.3. Price impact asymmetry and past price movement

We next test Hypothesis 1 on how institutional constraints captured in price run-up history affect price impact asymmetry (Saar, 2001). Although we test directly, the precise relations between asymmetry and price-run predicted by Saar (2001) in this paper, we also verify Saar's assumption that price-run ups are indeed associated with institutional constraints[6] in our Online Appendix.

With the price history group carefully defined, we first present the raw permanent price impact for each price history group in Panel A of Table 3 using the three different post-trade price benchmarks (t+1, t+5, and t+10). For each of the three post-trade price benchmarks, we calculate price impact of buys, the price impact of sells, and the asymmetry between those two.

For raw PPI_{t+1} in Panel A, the price impact of buy (sell) orders is a decreasing (increasing) function of the length of a price run-up. Buy orders arriving during the early stages of a price run-up experience a higher permanent price impact than those arriving at later stages of the run-up. The price impact is 89 bps with a 1-day run-up and drops to 77 bps with +2 to +5 days of run-up. After a prolonged run-up of 6-10 days, the price impact of buys drops further to 27 bps. The monotonic decline in the price impact of buys is consistent with the notion that it becomes more difficult for institutional investors with information to buy as the capital and diversification constraints become more binding as we move from the early to the later stages of a price run-up.

[6] Specifically, following the method in Chakrabarty, Moulton, and Trzcinka (2017) to construct holdings, we confirm that institutions buy more at the initial stages of a price run-up when their holding in the stock is still low and they face short-selling constraints. In contrast, the sell imbalances are the highest after a long price run-up when institutions face capital constraints and diversification constraints because they already have a sizable holding in the stock. We thank an anonymous referee for this suggestion.

With a longer price run-up, buy imbalances are less informed and could represent herding behavior instead of information.

The pattern of the permanent price impact of sells is opposite to that of buys. Consistent with the arguments in Hypothesis 1, the price impact of sells increases with the length of the price run-up. This is because as institutions accumulate inventory in the presence of a price run-up, the short-selling constraints that institutional investors initially faced becomes less binding. The price impact is 32 bps after a 1-day price run-up and it increases to 90 bps for sells in stocks with 6-10 days of consecutive price increases. This is an indication that informed institutional selling is less constrained after a long price run-up and generates a larger permanent price impact.

We synthesize the results for buys and sells by reporting the price impact asymmetry, which is positive for stocks that are at the earlier stages of a price run-up. As the length of a price run-up increases, the price impact of sells increases substantially while the price impact of buys decreases substantially. Thus, the price impact asymmetry becomes negative after a prolonged price run-up. The last row of Panel A, reports statistical significance tests for the difference between the price impact asymmetry of the last group (+6 to +10) and the first group (+1). The difference between the two is -120 bps and is statistically significant at the 5% level, which is consistent with Hypothesis 1.

The relation between the market-adjusted permanent price impact of buys and sells, and the asymmetry between buys and sells conditioned on price history, is plotted in Figure 1. It displays the reduction in asymmetry in price impact with the increase in the price run-ups. At the beginning of a price run-up, the market-adjusted price impact is 89 bps for buys and 51 bps for sells. But after ten days of price run-up, the difference flips, with buys having a price impact of 35 bps compared to 105 bps for sells. For the price history ranging from +1 day to +10 days, we see a clear trend that the price impact of buys (sells) declines (increases) as the streak of consecutive positive price changes increases from +1 day to +10 days.

At the beginning of a price run-up, the conventional wisdom of Chan and Lakonishok (1993) and Keim and Madhavan (1995) applies; they suggest that price impact is mainly a function of the direction of trades, and that asymmetry is always positive. However, our novel empirical finding is consistent with the model of Saar (2001) that price history matters, and with long enough price run-ups, price impact asymmetry is generally negative. Thus, the information content of institutional trades can only be assessed after understanding institutional trading behavior and constraints. One can clearly see that between +3 and +4 of the price run-ups that the price impact for buy imbalances becomes less than the price impact for sell imbalances and keeps decreasing.

Table 3. The reduction of price impact asymmetry

The Table shows the permanent price impact asymmetry based on past price run-up of 1 day, 2-5 days, or 6-10 days. We report results with three values of *n* to measure PPI 1, 5, and 10 days after institutional trade imbalance. We average price impact across stock days for each group, and weighted by institutional trading imbalance. Asymmetry for each price history group is defined as the difference between the permanent price impacts of buy imbalances and sell imbalances. The net institutional trade price impact, *NPPI = Raw Permanent Price Impact –Control PPI.* On a given day, stocks not traded by institutional investors become part of the control set and we calculate their price Impact. NPPI is the price impact of stocks traded minus the average price impact of stocks not traded. We calculate *t-statistics* using standard errors adjusted with the Newey-West (1987) procedure. *, ** indicate significance at 1% and 5% levels. The number of stock-day observations is 2,869,304.

Price Run-Up History	*PPI t+1*			*PPI t+5*			*PPI t+10*		
	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry
Panel A: PPI									
1	0.89	0.32	0.57*	0.93	0.23	0.71*	1.19	0.17	1.02*
+2 to +5	0.77	0.60	0.18**	0.83	0.41	0.41**	0.92	0.48	0.43
+6 to +10	0.27	0.90	-0.63*	0.37	0.88	-0.51**	0.45	1.02	-0.76**
Magnitude of Reduction (+6 to +10 minus +1)			-1.20*			-1.21*			-1.78*
			(4.58)			*(4.29)*			*(3.86)*
Panel B: MPPI									
1	0.88	0.45	0.43*	0.86	0.39	0.46*	0.95	0.19	0.75*
+2 to +5	0.76	0.69	0.09	0.77	0.47	0.29	0.77	0.61	0.16
+6 to +10	0.31	0.98	-0.67**	0.20	1.01	-0.81**	0.34	1.31	-0.96**
Magnitude of Reduction (+6 to +10 minus +1)			-1.11*			-1.27*			-1.72*
			(3.29)			*(3.45)*			*(3.23)*
Panel C: BPPI									
1	0.86	0.48	0.38*	0.79	0.44	0.34**	0.80	0.28	0.52**
+2 to +5	0.76	0.70	0.05	0.80	0.51	0.29	0.75	0.66	0.09
+6 to +10	0.38	0.93	-0.56**	0.17	1.13	-0.95**	0.23	1.44	-1.22**
Magnitude of Reduction (+6 to +10 minus +1)			-0.94*			-1.30*			-1.73*
			(3.80)			*(3.20)*			*(3.13)*
Panel D NPPI									
1	0.95	0.35	0.60*	0.97	0.26	0.71*	1.22	0.14	1.09*
+2 to +5	0.90	0.51	0.40*	1.02	0.20	0.82*	1.15	0.19	0.96*
+6 to +10	0.56	0.78	-0.22	0.56	0.71	-0.15	0.60	0.78	-0.18
Magnitude of Reduction (+6 to +10 minus +1)			-0.82*			-0.85**			-1.27*
			(3.15)			*(2.36)*			*(2.58)*

We also examine Hypothesis 1 with alternate post-trade windows of either 5 or 10 days. The direction and significance of the results are generally consistent across all three windows. In Panels B and C of Table 3, we report market-adjusted and beta-adjusted permanent price impact, respectively. Our results are qualitatively similar to what we report in Panel A of Table 3.

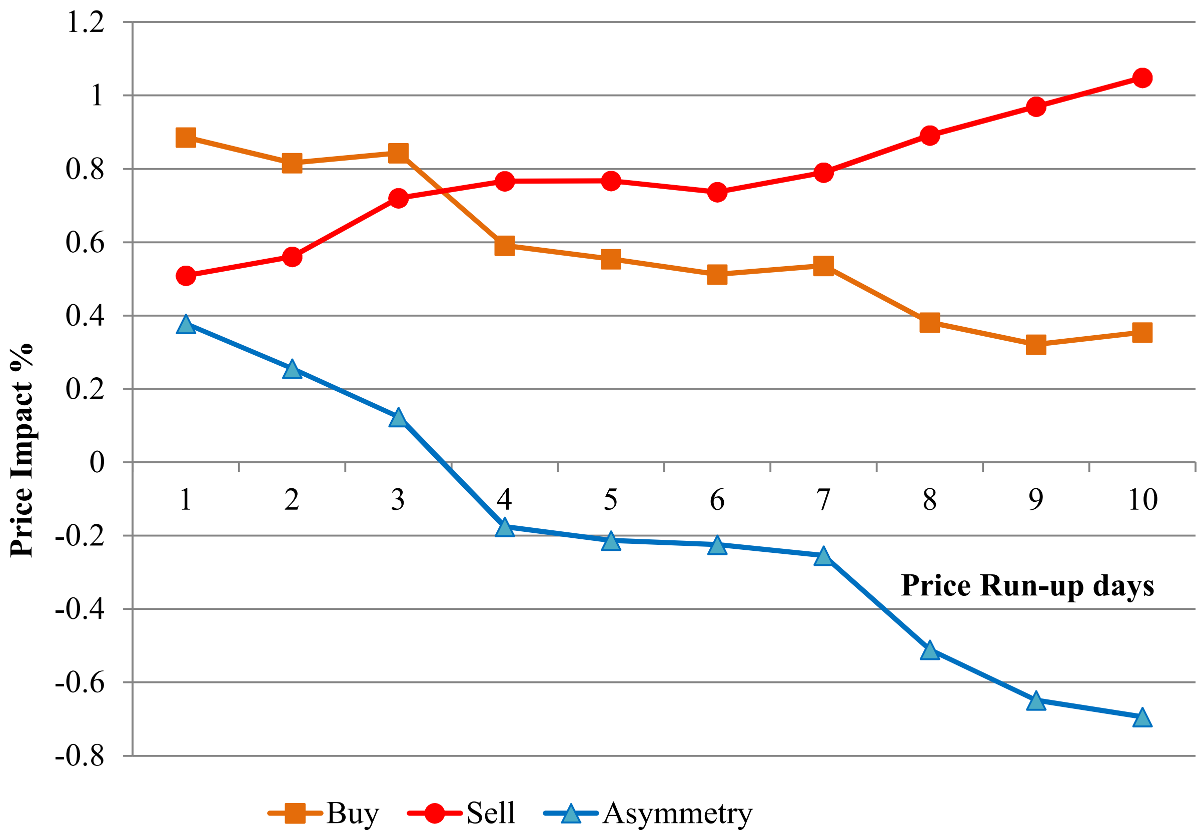

Figure 1: Price impact asymmetry and price history. In this figure, we plot NPPI defined as raw permanent price impact minus the NIT (no institutional trade) price change for matching number of price run-up stock-days. We plot NPPI for institutional buy imbalances, institutional sell imbalances, and the asymmetry between buy and sell imbalances on the vertical axis. Price impact asymmetry is the difference between NIT-adjusted buy and sell price impacts. Raw price impact is calculated as the stock return from one day before the order arrival to one day after the last trade in that order. Price history on the horizontal axis ranges from 1 day of price run-up to +10 days of consecutive price run-ups.

Lastly, we report *NPPI* (no institutional trade-adjusted net permanent price impact) specified in equation 4 in Panel D of Table 3. Our no institutional trade-adjusted measure of price impact removes the effects of price reversal that may be unrelated to institutional trading by deducting the corresponding no-trade price changes from the raw *PPI*. These are control stocks that have undergone similar price patterns (witnessed the same number of days of price run-up as the treatment sample), but were not traded by institutional investors in our sample. Thus, we are able to extract the pure effects of institutional trading. We continue to find price impact asymmetry results consistent with Hypothesis 1. Thus, our findings of changing price impacts and the resulting asymmetry for different price history groups are consistent with the notion that institutions are asymmetrically constrained in exploiting their information during the course of a price run-up. Since *NPPI* can best isolate the pure permanent price impact of institutional trades by removing price changes unrelated to institutional trading, we use *NPPI* in the remainder of our analyses.

In addition to the results reported in Figure 1 and Table 3, we also attempt to quantify the economic significance of our results. It is clear from some basic calculations of institutional dollar turnover presented in the Online Appendix that the asymmetry is not only statistically significant, it also has a profound impact on market valuation.[7]

[7] As a quick summary of the Online Appendix, buy trades move the prices up by 0.89% (taken from Table 3, Panel A), which represents an upward revision in value of $43.32 million in total based on 186,318 shares bought on stock days with buy imbalances. The sells averaging 53,124 shares on such days move prices down 0.32%, which represents a downward revision of valuation at $4.44 million. This pattern completely flips after a long price run-up. The asymmetric permanent price impact response suggests that Ancerno institutions' trades have changed the valuation of the traded stocks very differently depending on whether they are buying or selling.

4.4. Price impact asymmetry and informational variables

We demonstrate the importance of informational variables such as idiosyncratic stock volatility, analyst forecast dispersion, trading intensity, and stock price dispersion in Table 4. Our general approach is to form high and low information asymmetry portfolios using the 4^{th} and the 1^{st} quartiles, respectively. The results are robust when using medians instead of quartiles as cut-offs for forming groups based on information asymmetry (not tabulated here but available upon request). We also conduct multivariate regression analysis (reported in Table 6) using the actual values of these variables for each stock-day.

4.4.1. Price impact asymmetry and idiosyncratic volatility

Panel A1 of Table 4 reports price impact asymmetry based on idiosyncratic volatility (*IVOL*) and price history. First, price impact asymmetry monotonically decreases as a price run-up becomes longer for both the high and low *IVOL* groups, which is consistent with Hypothesis 1 that after a prolonged price run-up, the price impact asymmetry between buys and sells becomes less positive or even negative. Second, the price impact asymmetry is higher for high *IVOL* stocks than for low *IVOL* stocks. A closer look at the price impact conditioned on price history also shows that the higher price impacts of informed buys after an initial price run-up and that of sells after an extended price run-up are the main drivers for the price impact asymmetry patterns. Both these findings are consistent with Saar's (2001) model and Hypothesis 2a.

Table 4. Price impact asymmetry: price run-up and information variables

Permanent price impact $NPPI_{t+1}$ and asymmetry variables retain their definition from previous tables. We present the information for high and low information asymmetry groups based on four different information variables - stock idiosyncratic volatilities in Panel A, analyst forecast dispersion in Panel B, trading intensity in Panel C, and price dispersion in Panel D. Within each panel, we form high and low portfolios using the 4^{th} and 1^{st} quartiles as cut-off points. We calculate *t-statistics* using standard errors adjusted with the Newey-West (1987) procedure and presented in parentheses. *, ** indicate significance at 1% and 5% levels respectively. The number of stock-day observations is 2,416,369.

Price Run-up	High (4^{th} quartile)			Low (1^{st} quartile)		
	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry
Panel A: Idiosyncratic Volatility						
1	1.22	0.33	0.90*	0.70	0.38	0.32*
+2 to +5	1.27	0.71	0.56	0.77	0.33	0.43*
+6 to +10	0.44	1.15	-0.71	0.67	0.48	0.19
Magnitude of Reduction (+6 to +10 minus +1)			-1.60*			-0.13
			(3.49)			*(0.63)*
Panel B: Analyst Forecast Dispersion						
1	1.51	0.37	1.14*	0.62	0.29	0.33*
+2 to +5	1.44	0.68	0.75*	0.67	0.27	0.40*
+6 to +10	0.75	1.17	-0.43**	0.50	0.95	-0.45
Magnitude of Reduction (+6 to +10 minus +1)			-1.57*			-0.78*
			(6.25)			*(2.93)*
Panel C: Trading Intensity						
1	1.40	0.68	0.72*	0.54	0.29	0.25*
+2 to +5	1.30	0.49	0.80*	0.38	0.22	0.16**
+6 to +10	0.80	0.89	-0.09	0.36	0.28	0.08
Magnitude of Reduction (+6 to +10 minus +1)			-0.80*			-0.17
			(3.32)			*(0.79)*
Panel D: Price Dispersion						
1	1.81	0.18	1.63*	0.39	0.39	-0.00
+2 to +5	1.57	0.68	0.89*	0.56	0.22	0.34*
+6 to +10	0.33	0.74	-0.41*	0.38	0.47	-0.08
Magnitude of Reduction (+6 to +10 minus +1)			-2.04*			-0.08
			(4.27)			*(0.20)*

4.4.2. Price impact asymmetry and analyst forecast dispersion

The dispersion among analysts about forecasted earnings is larger when information is heterogeneous or unevenly distributed. Thus, disagreement among analysts is an indication of a lack of publicly available information and can be used to form a metric of the degree of information asymmetry about a firm's prospects.[8] We define analyst forecast dispersion as the standard deviation of the earnings forecast scaled by the share price. We form our portfolios of high and low information asymmetry groups using observations in the 4^{th} and the 1^{st} quartiles.

Results on the relation between permanent price impact asymmetry, analyst forecast dispersion, and price history are reported in Panel B of Table 4. We see strong support for Saar's (2001) hypothesis that asymmetry is more severe for stocks with high analyst forecast dispersions for shorter price run-ups. Likewise, the reduction in asymmetry is indeed much stronger for the high analyst forecast dispersion group than for the low analyst forecast dispersion group after prolonged price run-ups. Within each subgroup based on the dispersion of analyst forecasts, we continue to observe the highest information content in institutional buys (sells) after a 1-day price run-up (+6 to +10 days of run-ups). For instance, sells after 6-10 days of run-ups have *PPI* of 117 bps for stocks with higher forecast dispersions, versus only 95 bps for stocks with lower forecast dispersions.

The difference between the asymmetry after 6-10 days of price run-ups and the asymmetry after 1-day of price run-ups shows a reduction in the buy price impact and an increase in the sell price impact and is consistent with the hypothesized reduction in asymmetry. Also, consistent with

[8] Lang and Lundholm (1993, 1996) show that analyst forecast dispersion decreases as firms enhance information disclosure. Dispersions also decrease when analysts have access to conference calls (Bowen, Davis, and Matsumoto, 2002) and better access to management (Chen and Matsumoto, 2006).

Hypothesis 2a, the reduction in asymmetry is more pronounced at –157 bps for high analyst forecast dispersion stocks than the -78 bps for low analyst forecast dispersion stocks using the t+1 post-trade price benchmark. The direction is similar and the magnitude is stronger for other post-trade observation windows of t+5 and t+10 (not tabulated for brevity).

4.4.3. Price impact asymmetry and trading intensity

In Panel C of Table 4, we examine institutional trading intensity. For the shorter run-ups of 1 day or 2 to 5 days, we see that the price impact asymmetry is higher for stocks with high trading intensity. However, as a price run-up increases to 6 to 10 days, we see the asymmetry decline at a much faster rate for stocks with more intensive institutional trading, as predicted by Saar (2001). Taken together, these results provide support to Saar's theory and Hypothesis 2b. The difference row represents the reduction in price impact asymmetry. Consistent with Hypothesis 2b the difference in asymmetry between a long and a short price run-up is more extreme at -80 bps for high intensity stocks than the -17 bps for low intensity stocks using the t+1 post-trade price benchmark.

4.4.4. Price impact asymmetry and stock price dispersion

In Hypothesis 2b, we also posit that price impact asymmetry is higher for stocks with higher price dispersion at earlier stages of price run-ups, whereas this pattern is expected to be the opposite when stocks have extended price run-ups. The results reported in Panel D of Table 4 are consistent with the hypothesis. Initially, at the beginning of price run-ups, price impact asymmetry is larger for high price dispersion stocks (163 bps) than for low price dispersion stocks (0 bps). The reduction in the price impact asymmetry between 6-10 days of run-up and 1 day of run-up is more pronounced at -204 bps for stocks with high price dispersion than -8 bps for stocks with low price dispersion.

4.5. Price impact asymmetry and market condition

Our sample period from 2001 to 2012 contains both bull and bear periods. Chiyachantana et al. (2004) show that market conditions are important drivers of buy-sell asymmetry. Thus, before we perform our multivariate regression of the determinants of the price impact asymmetry, we perform a test to see if the documented pattern of asymmetry holds under different market conditions. We capture market condition with the monthly CRSP value-weighted index return, where a bull market is a month when the CRSP value-weighted index provided positive returns and the bear market is when the CRSP value-weighted index had negative returns. In general, price impact is expected to be amplified when the trades are in the direction of the market movement (i.e., buys in bull markets and sells in bear markets) and subdued when trades are in the opposite direction. We report our results in Table 5. As expected, our results are highly robust to market conditions. Market conditions do play a role in the sense that for any level of price run-up, buy price impact in bull markets is higher than buy price impact in bear markets; similarly, the sell price impact is generally higher in bear markets. But the reversal of the asymmetry with price-run up holds in both bull and bear markets. Thus, we can conclude that the institutional constraints in Saar (2001) theory are at play in both bull and bear markets and have significant incremental power in explaining price impact asymmetry over and above that caused by market conditions.

Table 5. Price impact asymmetry: market condition
NIT adjusted permanent price impact PPI_{t+1} (*NPPI*) and asymmetry variables retain their definition from previous tables. We present the information for bull and bear markets, where we define a bull market as months when the CRSP value-weighted index provided positive returns and the bear market is when the CRSP value-weighted index had negative monthly returns. We calculate *t-statistics* using standard errors adjusted with the Newey-West (1987) procedure and presented in parentheses. *, ** indicate significance at 1% and 5% levels respectively. The number of stock-day observations is 2,416,369.

Price Run-up	Bull			Bear		
	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry
1	0.97	0.16	0.81*	0.82	0.55	0.26**
+2 to +5	0.99	0.26	0.73*	0.74	0.69	0.04
+6 to +10	0.49	1.01	-0.52**	0.43	0.91	-0.48**
Magnitude of Reduction (+6 to +10 minus +1)			-1.33*			-0.74*
			(5.58)			(3.03)

4.6. Multivariate regression of permanent price impact

Finally, we examine the determinants of price impact on both a stand-alone basis and interactive basis, in a multivariate regression for institutional trades. We use a dummy variable *Buy* which equals 1 for all stock-days with buy imbalances and 0 for all stock-days with sell imbalances. The regression equation is:

$$NPPI_{t+n} = \beta_0 + \beta_1\, Buy\ Dummy + \beta_2\ Price\ History + \beta_3\, Analyst\ Dispersion + \beta_4\ (Buy\ Dumy * Price\ History) + \beta_5\ (Buy\ Dummy * Analyst\ Dispersion) + \beta_6\, (Buy\ Dummy * Analyst\ Dispersion * Price\ History) + \beta_7\, Firm\ Size + \beta_8\, Market\ Condition + \beta_9\, Inverse\ of\ Stock\ Price + e_t. \tag{6}$$

Where the dependent variable *NPPI* is the adjusted permanent price impact of the institutional trade defined in equation 4, and *Price History* is the number of days that a stock has experienced positive excess return. Because *Analyst forecast dispersion* has been widely used as a direct measure of the information asymmetry, and plays a significant role in our univariate analysis, we choose to include it in our multivariate analysis to represent the intensity of information asymmetry. Our results hold with other information asymmetry proxies (idiosyncratic volatility, trading intensity, and price dispersion) as well, but are not tabulated for brevity.

Our multivariate analysis involves building the model stepwise. In line with conventional wisdom, the regressions specification includes the buy imbalance dummy, *Buy*, which is expected to be positive. Next, *Price History* helps build the test of Saar's theory. The variable of interest is the interaction term between *Buy* and *Price History*, which allows us to explicitly test Hypothesis 1 of declining price impact asymmetry with an increase in price run-up. The results reported in Table 6 (column labeled as Hypothesis 1) first confirm that stocks with buy imbalance generally have a higher price impact in line with the conventional wisdom. But more importantly, this *Buy* effect is weakened when there is a long *Price History* of run-ups, as the coefficient for the interaction term is negative -0.110 and is highly significant. This is consistent with the Hypothesis 1 as the asymmetry of price impact shifts from highly positive to less positive or even negative when there is a long price run-up.

We proceed to test Hypothesis 2 by adding *Analyst Dispersion*, the two-way interaction of *Buy* and *Analyst Dispersion*, and the three-way interaction among *Buy, Price History* and *Analyst Dispersion*. We report results in the column 2. As expected, the coefficient for the interaction between *Buy* and *Price History* remains negative and significant per Hypothesis 1. Additionally, we find, a higher degree of Information Asymmetry is associated with a higher price impact and that effect is stronger when interacted with the *Buy dummy*, consistent with Hypothesis 2. The three-way interaction coefficient is negative, suggesting that the asymmetry in stocks with a higher degree of information asymmetry will see a reversal when the there is a long price run-up. While the direction is consistent with Hypothesis 2, this effect is not significant in this baseline model. To ensure that our model estimates do not suffer from bias due to omitted variables, we add control variables such as *Market Condition, Firm Size* and *Inverse Stock Price* that are known to be important determinants of the asymmetry. Following Chiyachantana et al. (2004), we measure market condition with the monthly CRSP value-weighted index return. We expect to see that price impact asymmetry to be amplified when the trades are in the direction of the market movement (i.e., buys in bull markets and sells in bear markets) and subdued when trades are in the opposite direction. In addition, Chan and Lakonishok (1995) and Keim and Madhavan (1997) show that institutional price impact is negatively correlated with a stock's market capitalization, and positively correlated with relative price, so we include all these factors as control variables in our analysis. We report results from our full model specification in column 3.

We continue to see that the interaction between *Buy* and *Price History* is negative and significant. The negative coefficient implies that the longer the price run-up, the lower the asymmetry, which is what Saar (2001) predicts would happen when informed institutions face dynamic constraints. Once proper control variables are included in the model, the coefficient for the three-way interaction is negative and significant, suggesting that the asymmetry in stocks with a higher degree of information asymmetry will see a reversal when the there is a long price run-up, consistent with Hypothesis 2. Thus, taken together, our results offer strong support to both hypotheses on price impact asymmetry stemmed from the theoretical model of Saar (2001).

Table 6. Regression results

The table shows the regression results where the dependent variable is *NPPI* defined as Raw Permanent Price Impact minus the *NIT* (No Institutional Trade) price change for matching number of price run-up stock-days; *t+n* denotes the Permanent Price Impact after n days. We use Market condition, which is the one-month value weighted CRSP return, Firm Size (log of market capitalization) and the inverse of stock price as control variables. Statistical significance is indicated by * for 1% levels, ** for 5% levels and *** for 10% levels.

	(1) $NPPI_{t+1}$	*(2)* $NPPI_{t+1}$	*(3)* $NPPI_{t+1}$	*(4)* $NPPI_{t+5}$	*(5)* $NPPI_{t+10}$
Intercept	0.252*	0.287*	-0.069	-0.012	-0.198***
Buy dummy	0.711*	0.621*	0.232*	0.404*	0.671*
Price History	0.069**	0.067*	0.041*	0.046*	0.051*
Buy dummy x Price History	-0.110**	-0.109**	-0.091*	-0.092*	-0.111*
Analyst Dispersion		0.039**	0.099**	0.068**	0.076***
Buy Dummy x Analyst Dispersion		0.095*	0.089*	0.093	0.079
Buy dummy x Price History x Analyst Dispersion		-0.014	-0.004*	-0.092*	-0.009
Firm Size			-0.007	-0.003	0.004
Market Condition			0.065*	0.009*	0.015*
Inverse of Stock Price			-0.017*	-0.019*	-0.018*
N	2,412,220	2,412,220	2,412,220	2,412,220	2,412,220
Adj. R^2	0.002	0.003	0.004	0.004	0.005

We also run the regression with *NPPI* for *t*+5 and *t*+10 days with the same set of independent variables in columns 4 and 4 respectively and find that the main result remains robust when permanent price impact is measured at these points after the institutional trades. We find that the asymmetry is larger at the initial stage of a price run-up, and the reduction in asymmetry is also more pronounced after a long price run-up. However, the effects of analyst dispersion in sharpening the asymmetry is not statistically significant at these longer horizons.

The coefficients on control variables are consistent with prior research. The contemporaneous market condition variable has a statistically significant positive coefficient, implying that price impact asymmetry is positive in bull markets and negative in bear markets. Price impact is not significantly affected by market capitalization, but negatively affected by the inverse of stock price.

4.7. Robustness tests

In this subsection, we show that our inferences about the information content of institutional trades are robust to a variety of alternative definitions for price run-ups, and price impacts. We also discuss several alternative explanations of our findings.

4.7.1. Price impact asymmetry on event days

Net trading volume might include a number of non-event days (trading days without meaningful institutional volume). To further examine how price impact asymmetry relates to price history and constraints on event days, we identify abnormal net volume event days.[9] We

[9] We thank an anonymous referee for this suggestion.

compute the average net volume for each stock based on its trades in the previous 60 trading days on a rolling basis. We define an event day as an abnormal volume stock-day where the absolute net trade volume exceeds the average. This gives us 1.4 million abnormal institutional trading activity stock days. We then compute the *NPPI* net buy and net sell stock-days given their price run-up history. We report the results for this sub-sample in panel A of Table 7. Our results remain robust for this sample of event days. We also compute event days based on abnormal CRSP volume. We classify days on which stocks traded (by the entire market) more than the average of the last 60 trading days as event days. We have 0.97 million such event days. The results reported in Panel B of Table 7 are still consistent with the results for the entire sample.

4.7.2. Orders executed on the same day

Although 86% of our sample orders are executed on the same day, the rest take multiple days to execute. We expect that our daily trade imbalance measures are not affected by the length of order execution. Nonetheless, as a robustness test, we exclude all orders that are executed over multiple days. The conclusions about asymmetry and its reduction with price run-up remain the same. For example, *NPPI* asymmetry for a 1-day run-up is 67 bps when our sample is restricted to trades completed within a single day compared to 60 bps for all orders in Panel D of Table 3 and the reversal for t+1 is -59 bps for this sample compared to -82 bps in Table 3. Results are not reported for brevity but available from the Online Appendix.

Table 7. Price impact asymmetry on abnormal volume days

The table shows permanent price impact asymmetry for abnormal volume event days. NPPI and Price History retain their definition from previous tables. In Panel A, we compute abnormal volume stock-day events based on trades from our sample. If the absolute net trade volume in a stock exceeds its average trading volume in the last 60 trading days, we classify the stock-day as an abnormal volume event. We have 1.4 million such events. In Panel B, we identify abnormal volume event day based on CRSP volume. We classify stock-days on which stocks traded (by the entire market) more than the average of the last 60 trading days as abnormal volume event days. We have 0.97 million such events. *,** indicate significance of 1% and 5% and we calculate *T-statistics* using standard errors adjusted with the Newey-West (1987) procedure and presented in parentheses.

Price History	*NPPI t*+1			*NPPI t*+5			*NPPI t*+10		
	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry
Panel A:									
1	0.95	0.33	0.62*	0.97	0.25	0.73*	1.11	0.17	0.95*
+2 to +5	0.93	0.45	0.48*	0.99	0.16	0.83*	1.14	0.03	1.11*
+6 to +10	0.50	0.57	-0.07	0.56	0.54	0.02	0.46	0.78	-0.32
Magnitude of Reduction (+6 to +10 minus +1)			-0.69**			-0.71**			-1.27*
t-stat			*(2.43)*			*(2.00)*			*(3.54)*
Panel B:									
1	1.28	0.26	1.03*	1.35	0.11	1.24*	1.61	0.15	1.46*
+2 to +5	1.25	0.35	0.90*	1.34	0.21	1.13*	1.54	0.20	1.33*
+6 to +10	0.55	0.52	0.03	0.56	0.34	0.22	0.66	0.66	0.00
Magnitude of Reduction (+6 to +10 minus +1)			-1.00*			-1.02**			-1.46**
t-stat			(2.86)			(2.21)			(2.55)

4.7.3. Alternative explanations

Our results are driven by the asymmetric use of positive and negative information by institutions. However, alternative explanations may be plausible for the results we find. For example, prior works suggest that the decrease in total price impact (sum of temporary and permanent price impacts) of buy trades could be due to portfolio rebalancing (Calvet, Campbell, and Sodini, 2009) or disposition effect (Frazzini, 2006). Portfolio rebalancing refers to institutions' periodic rebalancing by selling winners. The disposition effect refers to the tendency of investors to sell stocks whose prices have increased. Both are relatively mechanical decisions, unlike the informed institutional trading and related constraints explored in Saar's (2001) model of price run-up. Because rebalancing and disposition sells are not information related, they may only lead to a temporary price impact but not permanent price impact as we have reported. The permanent price impact of sells isolate and rule out the alternative explanations and indicates unconstrained use of negative information by institutions, when no longer constrained by short selling constraints because a stock is now held in institutions' portfolios. Furthermore, Barberis and Xiong (2009) that characterize the disposition effect as "[o]ne of the most robust facts about the trading of individual investors," not institutional traders.

5. Conclusion

Using a comprehensive dataset from Ancerno for the 2001-2012 period, we extend the literature on price impact asymmetry by scrutinizing the effects of individual stock price history on the information content of institutional trades. This is the first empirical test of Saar's (2001) theoretical model concerning the asymmetric use of information by institutional traders under changing constraints – namely, capital, diversification, and short selling constraints – at different stages of price run-ups. By focusing on total imbalances, we are able to capture the reality of institutional order splitting in the current market structure. We also adjust our measures for the return patterns related to price history but unrelated to institutional trades (our no institutional trade control sample) to rule out the alternative explanation that asymmetry is due to return reversals.

We find that price impact asymmetry is a function of the history of stock prices as well as the informational characteristics of stocks, and market condition. Price impact asymmetry in stocks at earlier stages of price run-ups is generally positive. After prolonged price run-ups, permanent price impact asymmetry reverses and ultimately becomes negative. Our results are consistent with the notion that the asymmetry of permanent price impact directly depends on changing institutional constraints. During the initial stages of a price run-up, the short-selling constraint is binding but not the capital and diversification constraints. As the duration of a price run-up becomes longer, the capital and diversification constraints are more likely to bind and institutions are less likely to face the short-selling constraint. In addition, price impact asymmetry is affected by informational variables, such as idiosyncratic volatility, analyst forecast dispersions, trading intensity, and price dispersions. Stocks with higher information asymmetry also experience a larger reduction in the price impact asymmetry after prolonged price run-ups.

Our findings suggest that institutional trading performance, which eventually impacts portfolio return performance, can be significantly affected by the direction and the timing of trades in relation to the price history and informational characteristics of individual stocks. Our analysis of the permanent price impact of institutional trading suggests that institutions are in fact informed, and their trades update the valuation of traded stocks. Our findings help us gain a better understanding of how prices respond to information and institutions' ability to trade on that information.

Appendix

A1. Portfolio Holdings Conditioning on Price History

Understanding not only how institutions trade, but their holdings in the stocks they transact certainly sheds light on the constraints articulated in Saar's (2001) model. However, this is a difficult task, as the Ancerno dataset contains no information on a fund's holdings at any time; only transactions are reported to Ancerno. Thus, we adopt the method similar to Chakrabarty, Moulton, and Trzcinka (2017 JFQA) by effectively initializing each symbol-clientcode combination with zero shares of holding.

We then build the initial first year holdings for each institutional client in our dataset. In order to build the holdings, we start from the date a client first appears in the dataset and then continue adding his buy trades for a year and subtracting his sell trades for the year. We treat the end-of-year holdings as the initial holding of the institutions. (For robustness, we also use a 2- year period to build initial holding and our results are qualitatively the same as those reported below.)

Next, to relate institutional constraints to their trading decisions, we compute the holdings of each client on each stock-day. Holding = Prior holding + Buy – Sell. We divide the stocks into five groups based on the market value of stock holding in the portfolio of each client every stock-day. Our main intent with the analysis is to understand how institutional investors trade, given their holdings and the price history of the stock. Our prior is that if they have high holdings in a stock, then they should be net sellers, (i.e., the trading imbalance on aggregate for institutions with high holdings should be negative). This imbalance should decline further as price run-up increases. We thus double sort the trade imbalance at the stock-day level for each institutional investor into five holdings groups and three price run-up groups.

We find that for all clients, holdings in quite a few stocks are negative. This happens mainly because we do not know the portfolio of the client when they first appear and we do not have data on IPO or SEO allocations, as they are not reported in Ancerno. As negative holdings are not feasible for institutions, we limit our attention to the subset of stocks that do have positive holdings based on our assumption to get a clearer picture. We report results in the Table A1.

Table A1. Institutional trading imbalances conditioning on price history and prior holdings (in shares)

		Holdings				
		Lowest =1	2	3	4	5=Highest
Price Run up	1 day	1820	1597	1,346	846	-571
	2 to 5 days	1684	1386	1,089	653	-851
	6 to 10 days	1434	1353	1,035	588	-1074

	D.F.	F Value	Pr. > F
Price run up	2	102.42	< 0.0001
Holding	4	18.61	< 0.0001
Price run up * Holding	8	5.08	< 0.0001

The results in Table A1 are consistent with the constraints faced by institutions as outlined in Saar's (2001) model. Institutions buy more at the initial stages of a price run-up when their holding in the stock is still low and they face short-selling constraints. In contrast, the sell imbalances are the highest after a long price run-up when institutions face capital constraints and diversification constraints because they already have a sizable holding in the stock. We run *t-tests* to confirm that the averages differences across pairs are different from zero and run a two- way F-test to confirm that the variation due to run up and holdings groups are statistically significant. By confirming that institutional constraints work in relation to price run-ups, just as assumed by Saar (2001), we have greater confidence in our main findings that permanent price impact asymmetry is associated with institutional capital, diversification, and short-selling constraints.

A2. Economic impact of findings on price impact asymmetry

For institutional trades, the most important component of transaction costs is the impact of the trader's own actions on the market. We present results to support to Saar's model (2001), which highlights the importance of the past price performance and institutional trading behavior in determining the price impact asymmetry.

Putting this in an economic perspective requires us to look at our sample more closely. In the Ancerno dataset itself, institutions trade 801 stocks on an average day. Their average stock price is $32.62. Consider the beginning of a price run-up. On the days with buy imbalances, 186,318 shares are bought. These buy trades move the prices up by 0.89% (taken from Table 3, Panel A) representing an upward revision in value of $43.32 million in total. The sells averaging 53,124 shares on such days move prices down 0.32%, representing a downward revision of valuation at $4.44 million. The asymmetric permanent price impact response suggests that Ancerno institutions' trades have changed the valuation of the traded stocks very differently depending on whether they are buying or selling. This is highly consistent with how institutions trade when they face short-selling constraints but no capital and diversification constraints.

What is striking from Saar's (2001) theory and our results is the reversal in price impact asymmetry. When we apply analogous calculation to institutional trading after 6-10 days of price run-up, we see the revaluation of share price due to institutional informed trades is mainly from their sells. As sells move price down by 0.90% on average, the downward revision of valuation is $46.91 million given that 199,471 shares sold on average on stock days with a sell imbalance. When we compute the value change for buys after 6-10 days of price run-up, with 57,039 shares traded and a price impact of 0.27%, the value increase only amounts to $4.02 million. Thus institutional informed sells have a much larger impact than buys after a long price run-up as the valuation changes likely reflect the relaxation of short-selling constraints and the onset of capital and diversification constraints.

Table A2 Economic impact:
The table shows the economic impact. We separate days based on buy and sell imbalances and compute the changes in valuation due to permanent price impact.

				Buy Imbalance				Sell Imbalance			
Price Run up (days)	Number of stocks	Average Market Cap ($ Billions)	Price	Average Volume	Price Impact (%)	Impact by Ancerno trades ($ Millions)	Market Wide Impact ($ Millions)	Average Volume	Price Impact (%)	Impact by Ancerno trades ($ Millions)	Market Wide Impact ($ Millions)
1	801	3.15	32.6	186,318	0.89	43.33	22,456	53,124	0.32	4.44	8,074
6-10	801	3.15	32.6	57,039	0.27	4.02	6,813	199,471	0.90	46.91	22,708

A3. Orders executed on the same day

Although 86% of our sample orders are executed on the same day, the rest take multiple days to execute. We expect that the length of order execution does not affect daily trade imbalance measures. Nonetheless, as a robustness test, we exclude all orders that are executed over multiple days. The conclusions about asymmetry and its reduction with price run-up remain the same. For example, *NPPI* asymmetry for a 1-day run-up is 67 bps when our sample is restricted to trades completed within a single day compared to 60 bps for all orders in Panel D of Table 3 and the reversal for *t*+1 is -59 bps for this sample compared to -82 bps in Table 3.

Table A3. Orders executed on the same day

We calculate the permanent price impact (*PPI*) of institutional trades, and the asymmetry, *PPI t*+*n*-= $\left(\frac{P_{t+n}}{P_{t-1}} - 1\right) * 100 * Direction$

All stocks traded by institutions on a day are classified as having an institutional buy or sell imbalance based on whether the institutional trading imbalance ($\sum_i Volume_{buy}$- $\sum_i Volume_{sell}$) is positive (direction=+1) or negative (direction=-1) respectively. The subscript t denotes the trade date when the trade is executed; P_{t+n} denote prices on dates *t*+*n*. We report results over three windows with values of *n* being 1, 5, and 10 days after the trade date. We define price history as the number of days of consecutive positive market-adjusted returns or run-up prior to the institutional trading order. Price impact is averaged across orders within each group, and weighted by institutional trading imbalance. We define price impact asymmetry (*PIA*) for each price history group as the difference between the permanent price impact of buys and that of sells. *T-statistics* based on standard errors adjusted with the Newey-West (1987) procedure are in parentheses. The number of stock-day observations is 2.46 million.

Price History	*PPI t*+1			*PPI t*+5			*PPI t*+10		
	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry	Buy	Sell	Asymmetry
Panel A: *PPI*									
1	1.00	0.33	0.67	1.06	0.28	0.78	1.21	0.32	0.89
+2 to +5	0.99	0.49	0.51	1.09	0.43	0.66	1.14	0.35	0.79
+6 to +10	0.67	0.59	0.09	0.77	0.79	-0.03	0.39	0.95	-0.55
Magnitude of Reduction (+6 to +10 minus +1)			-0.59			-0.81			-1.44
t-stat			(2.32)			(3.17)			(4.86)

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Chapter 2

Earnings expectations, forecasts, and the post earnings announcement drift

Abstract.

We provide a new explanation for the post earnings announcement drift (PEAD), one of the oldest market anomalies. We hypothesize that the PEAD results from information production and the drift observed in prices is a movement towards the changes in expectations and not an under-reaction or delayed response to the earnings announcement. We create a new measure that captures the changes in expectations over and above the earnings surprise. Our proxy is based on annual EPS forecasts by equity research analysts and takes into consideration both the responsiveness and the magnitude of the net changes in EPS forecasts. A long short trading strategy based on portfolios formed using our new measure generates higher returns compared to portfolios formed based on the earnings surprise measure. Most importantly, the earnings surprise based portfolio rankings loses its significance in explaining the PEAD when considered together with our new measure based portfolio ranking. Our results are robust to alternative risk adjustments, return computations, and controlling for factors known to be correlated with PEAD.

1. Introduction

Post-earnings announcement drift (PEAD) is described as the movement of a stock's cumulative abnormal returns to drift in the direction of an earnings surprise immediately following earnings announcement. Following a positive (negative) surprise, announced earnings exceeding (falling short of) the market's expectation of earnings, subsequent abnormal returns tend to be higher (lower) in the following periods. PEAD has been documented consistently in numerous papers for close to 50 years, and is one of the most resilient capital markets anomalies. Brennan (1991) addresses it as a "most severe challenge to financial theorists," and Fama (1998) names it "the granddaddy of all under reaction events." Three main explanations have been advanced for this anomaly: a failure to adjust abnormal returns for risk, a delayed response to earnings announcements (Bernard and Thomas 1989), and limit to arbitrage (Mendenhall, 2004, Sadka, 2006, Ng, Rusticus, and Verdi, 2008, and Chordia, Goyal, Sadka, Sadka and Shivakumar, 2008).

Recently, several studies have focused on whether analysts, as important information intermediaries, play a role in facilitating market reactions to earnings announcement and reducing investors' delayed response to earnings announcements. Analysts' earnings forecasts and stock recommendations can be valuable to the market because analysts are skilled at analyzing the value relevance of public information. Forecast revisions play an important role in the dissemination of information about corporate earnings. Because of their frequency and timeliness, these revisions have become a vital source of information. Specifically, analysts could have the ability to interpret the long-term implications of quarterly earnings and other financial data that firms report. Information produced by analysts helps investors better understand the news contained in earnings announcements and affects market's response to earnings announcements (Kim and Verrecchia 1994, 1997). Although there has been a significant shift in the timing of analyst forecast revisions to earnings announcements (Ivkovic and Jegadeesh 2004), there is little empirical evidence on the information role of these more- timely forecasts. Understanding how markets react to analyst forecasts issued during the earnings announcement window and the speed of price adjustment both during the announcement and drift windows is much needed. Zhang (2008) studies market reaction when analysts update their forecast within 1 trading day of the earnings announcement (bundled forecast). She reports a higher price response to an earnings surprise and attenuated PEAD in the presence of bundled analyst forecasts. Although the timeliness of the analyst's revision are considered in Zhang (2008), the content of the forecasts are not closely examined. Lobo, Song, and Stanford (2017) extend this line of research by including the interaction of the revision of analysts' forecasts of *annual* earnings with the information in the *annual* earnings announcements, i.e., whether the forecast revision reinforces or contradicts unexpected earnings. They find a significantly larger ERC when earnings announcements are accompanied by reinforcing analyst forecast revisions relative to both announcements with contradicting forecast revisions and those without announcement window forecast revisions. Separately, Balakrishna, Bartov and Faurel (2010) show profit / loss by a firm in addition to the earnings surprise can predict future stock price movement.

Built on prior research that look beyond information in the surprise by considering the actual magnitude of the responsive forecast revisions (0, +1), we propose a new measure – Net Analyst Forecast Revision (NAFR) based on annual EPS forecasts by equity research analysts and takes into consideration both the responsiveness and the magnitude of the net changes in EPS forecasts, upon announcements of quarterly earnings. Our new and improved measure of information production around earnings announcements captures not only the current information, but also expectations of future price movement. The measure, compares the changes in analyst expectations before and after earnings announcement to gauge at how analysts update their expectations about the firm following the announcement. Since our interest lies in explaining the drift we remove the current surprise as this information is already revealed to the market and the analyst. Finally, we standardize the measure by dividing it by the share price. Our study is closely related to Lobo et al (2017) but differs from their work in three important ways. First, we consider quarterly updates of year t+1 EPS forecast, while their research design only includes updates on year y+1 EPS when year t earning is announced. Thus, our sample is much larger and incorporates more frequent timely revisions of the analyst's forecasts. Second, our measure not only considers the direction of the forecasts, but also the magnitude. A forecast revision in the same direction of the earnings surprises can differ in magnitude and in their information contents. Our measure also is cleaner and more precise as we consider the net change in forecast revision by excluding the portion of revision that is due to the surprise in the quarterly earnings just announced. Third, although Zhang (2008) looks at responsive forecasts and the market reaction in the short (ERC) and longer windows (PEAD), Lobo et al (2017) only study the earnings return relations in the event window. If markets are efficient in processing private information generated through analysts forecast revisions, ERC is expected to be higher and PEAD to be attenuated for the subsample of responsive revisions (Zhang, 2008). However, analysts are more likely to revise their recommendations on earnings announcements for firm-quarters in which share prices are more misvalued (Yezegel, 2015). Further, market participants may discount the information in analysts EPS revisions and only partially incorporate it into share prices. It is therefore unclear whether earnings announcements with timely revisions result in a higher or lower post-earnings announcement returns. Thus while there is general consensus on how market reacts in short-term, the implications of our NAFR based on bundled forecast presents an opportunity to reexamine the PEAD.

We show that the post earnings announcement drift is better explained by changes in analyst expectations than by the earnings surprises. A long short trading strategy based on portfolios formed using our new measure generates higher returns compared to portfolios formed based on the earnings surprise measure. Most importantly, the earnings surprise based portfolio rankings loses its significance in explaining the PEAD when considered together with our NAFR based portfolio ranking. The abnormal returns from the hedged portfolio is primarily associated with the long positions, making it less likely to be explained away by the lack of liquidity and higher transaction costs often seen on the short position. Our results are robust to alternative risk adjustments, return computations, and controlling for factors known to be correlated with PEAD.

2. Literature review and motivation

Earnings announcements is by far one of the most important corporate event for firms and investors alike. Savor and Wilson (2016) show that earnings announcement premium is 9.9% annually. We start by proposing a new improved measure of information production around earnings announcements which captures not only the current information, but also how future expectations will be revised. In addition to earnings surprises, Balakrishna, Bartov and Faurel (2010) show that something as simple as a profit / loss by a firm in addition to the earnings surprise can predict future stock price movement. Thus, not all firms with a positive earnings surprise will witness a price increase. Sometimes if they miss revenue expectations or the management provides a downward guidance for the firm, the firm despite beating earnings will see share price fall. Because overall the announcement was not a good one for the firm.

Given that businesses are often complex and one measure, earnings, cannot summarize the financial performance of the firm. We propose an alternative measure which captures all the information in each announcement. Apart from insiders of the firm, equity analysts following the firm, know the most about the firm. They are best suited to process the announcement that the company comes out with since they have been actively following the company and its peers. To capture the change in expectation in a stock in the market, we turn to analyst forecast revisions. To calculate that we need to know their expectations before the earnings announcement and their expectations after the earnings announcement. However, there is one issue with the before and after measure. The quarterly eps forecast that the analysts provide for the current quarter cannot be compared to the forecast for the coming quarter, because of seasonality issues. Hence to overcome that we look at the annual forecast number that the analyst provides. For the fourth quarter, we look at the two years ahead forecasts. An analyst will read the entire earnings announcement carefully and will be able to synthesize that into information about future earnings expectations. If the firm did well on most fronts, then the analyst will update the annual expectation accordingly. Looking at the change between the annual eps expectation before and the eps expectation after the current quarterly earnings announcement is a valuable channel to understand the information content in the announcement. For example, if a company did well, and the analyst believes that the earnings expectations for the firm have improved, he might raise the annual eps target from $1 to $1.10. Our change in expectation measure will be equal to $0.1 in this case.

This measure still has one flaw. To understand it, let us follow a hypothetical example. Let us assume that we were in Q2 of 2017 and the firm announced its earnings yesterday and the analyst came up with his update today. When the analyst made his previous recommendation (maybe a month ago), he knew only the Q1 eps, and the annual forecast was the forecast for the next three quarters. Let us assume that Q1 eps was \$0.2 and his combined forecast for the remaining three quarters was 0.8, spread as \$0.25 for Q2, \$0.3 for Q3 and \$0.25 for Q4. The company managed to do better and had an actual eps \$0.3 (versus the analyst's forecast of \$0.25). Given the announcement and his analysis of the firm he raises his annual forecast to \$1.1. Now he predicts Q3 to be \$0.3 and Q4 to be \$0.3 as well. Note that even though the overall annual eps has increased by \$0.1, the improvement in Q3 and Q4 forecast is only \$0.05 (\$0.6 vs \$0.55 previously). The difference of \$0.05 is due to the earnings surprise in the current quarter (Q2). Hence the change in his expectation overall is Change in the annual eps expectation- earnings surprise in the current quarter. We standardize this by the stock price and arrived at our new measure. To overcome individual analyst's biases, we use the mean expectation before earnings announcement and the mean bundled expectation after earnings announcement. Since we want to explain the PEAD we need our new measure to be able to sort stocks into deciles one day after announcement. Hence, we restrict ourselves to firms that have bundled analyst announcements. The New measure (NAFR) for a firm j for the quarter t is defined as:

$$NAFR_{j,t} = \frac{\left(Mean\ Annual\ EPS\ Forecast_{j,t+1} - \ Mean\ Annual\ EPS\ Forecast_{j,t-1}\right) - \left(Quarterly\ Earnings\ Surprise_{j,t}\right)}{Share\ Price}$$

Now that we have our new measure we will use it in a similar fashion to the earnings surprise measure SUEj,t , which is calculated from the I/B/E/S database and it is the actual minus I/B/E/S mean forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter end.

First, we show that bundled forecasts have become extremely frequent and is one of the probable reasons for the reduction witnessed in the PEAD overtime. Several studies have shown that the PEAD has attenuated, but have not been able to clearly identify the reason for the reduction in the drift. We believe that the increased frequency of bundled forecasts has increased price discovery around earnings announcement. Zhang (2008), Zhang (2012) and Lobo, Song, and Stanford (2016) show the reduction in drift. Given that people associate the reduction in a market anomaly to increased efficiency, most explanations for the reduction in the magnitude of the drift have been attributed to increased market efficiency due to increased trading volume or high frequency traders. However, the reduction in the PEAD is directly attributable to increased bundling of information around the earnings announcement.

Next we show the characteristics and distribution of $NAFR_{j,t}$ are identical to that of $SUE_{j,t}$. We proceed to see how identical are the portfolios formed by the two measures and are surprised to see that even though there isn't a strong correlation between the ranking from the two measures, there is a stronger overlap between the portfolios of the top and bottom decile. Indicating that there is overlap between the SUE effect and the NAFR effect.

To show the superiority of the new measure we need to show that the profits from a trading strategy based on the creation of portfolios based on the new measure ranking outperforms a similar trading strategy based on the SUE effect. To demonstrate that our new measure reflects information over and beyond what is in earnings surprises, we include both adjusted SUE rank and adjusted NAFR rank as independent variables in explaining PEAD and see which variable has better explanatory power of the PEAD.

3. Data sources and research design

3.1. Data and key variables

We start with the detailed analyst files from the I/B/E/S database, and merge it with CRSP and Compustat databases. We start from the first quarter of 1995, because the I/B/E/S coverage prior to that is relatively sparse and continue till the first quarter of 2016. We use the following variables in our analysis:

$RESP_{i,j,t}$ = 1 if analyst i revises her forecast for quarter t+1 of firm j by trading day 1 relative to the earnings announcement of quarter t and 0 otherwise

$NRESP_{j,t}$ ($PRESP_{j,t}$) = the number (percentage) of analysts with $RESP_{i,j,t}$ = 1 among all analysts following firm j for quarter t.

$DRESP_{j,t}$ = an indicator variable that equals 1 if there is at least one analyst with RESPi,j,t = 1 for firm j quarter t and 0 otherwise.

CAR (-1, +1)$_{j,t}$ = the cumulative abnormal return for the three-day window (-1,+1) for firm j, centered on the earnings announcement date of the current quarter t.

CAR-Size adjusted abnormal return = the cumulated raw return minus the average return on an equal-weighted portfolio of the NYSE/AMEX/NASDAQ firm-size decile to which the firm belongs.

CAR-3 Factor abnormal return = the cumulated raw return minus the expected return for the stock calculated from the Fama French 3 factor model.

BHAR-Size adjusted return= the Buy and Hold raw return minus the return on an equal-weighted portfolio of the NYSE/AMEX/NASDAQ firm-size decile to which the firm belongs.

BHAR-3 Factor adjusted return = the Buy and Hold return minus adjusted for the expected return for the stock calculated from the Fama French 3 factor model

$LOGMV_{j,t}$ = log of market capitalization of firm j at the end of quarter t

$GUIDE_{j,t}$ = an indicator variable that equals 1 if firm j provides guidance for future earnings during the event window of quarter t and 0 otherwise, where corporate-issued guidance information is obtained from Thomson Reuters.

$Q4_{j,t}$ = an indicator variable that equals 1 if quarter t is the fourth quarter of the fiscal year for firm j, and 0 otherwise;

$SUE_{j,t}$ = calculated from the I/B/E/S data base and it is the actual minus I/B/E/S mean forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter end.

$BNEWS_{j,t}$ = an indicator variable that equals 1 if the unexpected earnings of firm j in quarter t is negative, and 0 otherwise

$COV_{j,t}$ =number of analysts following firm j for quarter t

3.2 Portfolio Formation and data preparation

To form portfolios, we need to rank all firms every quarter based on their earnings surprise. $RUE_{j,t}$ is calculated from rank given to the firm j based on its raw earnings surprise, $SUE_{j,t}$, ranked into deciles indexed from 0 to 9 every quarter and then the indices are divided by 9. We then subtract 0.5 to get the independent variable $RUE_{j,t}$, which ranges between -0.5 and 0.5. The slope coefficient in the regression of abnormal returns on the SUE decile rank (DSUE) may be interpreted as the return to a hedge portfolio that is long on the most positive SUE decile and short on the most negative SUE decile. We follow the same steps to create portfolios based on the New Measure and create the ranking RNAFR $_{j,t}$.

Our analyses require two return periods. To estimate the drift, we sum daily abnormal returns over the period from one trading day after the earnings announcement through the next 60 trading days. To measure the immediate short-term earnings announcement return we sum three daily abnormal returns, including the day preceding the earnings announcement date, the announcement date, and the following day.

Following standard elimination from previous literature we require that the share price at the end of the quarter is greater than $1. We stick to US only firms with share codes 10 and 11. The market cap of the firm should be available for the previous quarter and should be greater than $ 50 million. This eliminates small illiquid firms from our sample and we can slightly negate the limits to arbitrage type of arguments. We also winsorize most of our data at the 1 and 99 percentile levels to remove extreme observations driving our results.

3.3 Calculating the Drift

Consistent with prior literature (e.g., Bernard and Thomas, 1990; Bartov et al., 2000). Specifically, prior literature has adopted the following regression model to estimate the average abnormal return one can earn from the post-earnings announcement drift:

$$\text{CAR\_D}_{j,t} = \beta_0 + \beta_1 RUE_{j,t} + \varepsilon_{j,t} \ . \qquad (1)$$

The dependent variable CAR_Dj,t is the size-adjusted return over the drift window, and the independent variable RUEj,t reflects the deciles, as opposed to the raw values, of the unexpected earnings. More precisely, the raw unexpected earnings SUEj,t are ranked into deciles indexed from 0 to 9 by quarter and then the indices are divided by 9. Following this we subtract 0.5 to get the independent variable RUE$j,t,$ which ranges between -0.5 and +0.5. Thus, the coefficient on RUEj,t can be readily interpreted as the size-adjusted return one can earn over the drift window with a zero-investment portfolio strategy that takes a long position in the highest decile and a short position in the lowest decile. In another specification of the model we use the Fama French 3 factor expected return for the stock as the benchmark for calculating the abnormal return and cumulate these to get the CAR.

3.4. Drift in the presence of bundled forecast

To capture the effect of bundled analyst forecast and its effect on the PEAD, we estimate the following model.

$$CAR\_D_{j,t} = Year\ FE + \beta_1 RUE_{j,t} + \beta_2 RUE_{j,t}\ x\ DPRESP_{j,t} + \beta_3 DPRESP_{j,t} + \varepsilon_{j,t} \qquad (2)$$

We also estimate the same model with CAR adjusted for the Fama French 3 factor model. In order to check robustness we add several control variables and their interaction with the RUEj,t. control variables like Log of market capitalization, a dummy variable called Guide which equals 1 if the firm provides EPS guidance, 0 otherwise. COV, is the number of analysts covering the firm. BNEWS is a dummy variable which equal 1 if the firm had negative unexpected surprise. Q4 is an indicator variable which equals 1 if the quarter is the fourth quarter. We also have year fixed effects included in the regressions. Model 1 does not include the control variables and their interaction terms, whereas Model 1(a) does.

3.5 New Measure vs the SUE

For this part of our analysis we work with firms that have bundled analyst forecasts. This reduces our sample from 168,896 earnings announcements to 130,001 earnings announcements. Our goal is to find the main variable that explains the drift, whether it is SUE or NAFR. We already show that there is significant amount of correlation between the RUE and RNAFR and that the overlap is concentrated in the top and bottom deciles. So, to be able to identify the key driver, we add both variables as independent variables in the regression and see which has more explanatory power. This gives the specification for Model 2.

$$CAR\_D_{j,t} = Year\ FE + \beta_1 RNM_{j,t} + \beta_2 RUE_{j,t} + \varepsilon_{j,t} \tag{3}$$

We also test other specifications of the model by including all the controls and a specification which has only RNAFR as the main independent variable. These give us Model specifications 3 and 4.

4. Empirical results

4.1. Summary statistics

Table 1 provides the descriptive statistics for changes in analyst responsiveness over the years. We see that there is an overall increase in the number of analysts-firm-quarter observations every year. In 1995, we had only 18,232 analyst-firm-quarter and that number almost tripled to 61,910 analyst-firm-quarter observations. We also saw a big decline between the numbers of days it took to have the first analyst forecast out following an earnings announcement. On average, it reduced from 27 to 11 days. However, the number for the median firm fell drastically from 14 days to 1 day. This is clearly visible in the fact that for 97% of the firms in 2015, there was at least one analyst update within one trading day. Compared to only 49% firms in 1995 had one responsive analyst. In total, we had over 900,000 analyst announcements for over 260,000 firm quarters. The average number of analyst following a firm has also significantly gone up from 4.99 in 2015 to 11.62 in 2015. The number of analysts providing bundled forecast for a representative firm has gone up from 1 in 1995 to almost 8 in 2015.

Table 1: Descriptive Statistics of Analyst Responsiveness to earnings announcement
The data period is from the first quarter of 1995 to the first quarter of 2016. It covers 915,449 analyst announcements for 260,266 firm-quarters. $RESP_{i,j,t}$ equals 1 if analyst i revises her forecast for quarter t+1 of firm j by trading day 1 relative to the earnings announcement of quarter t and 0 otherwise. $NRESP_{j,t}$ ($PRESP_{j,t}$) is the number (percentage) of analysts with $RESP_{i,j,t} = 1$ among all analysts following firm j for quarter t. $DRESP_{j,t}$ is an indicator variable that equals 1 if there is at least one analyst with $RESP_{i,j,t} = 1$ for firm j quarter t and 0 otherwise.

Panel A

Year	# Analyst-Firm-Quarter	# Of trading days between earnings announcements and first subsequent forecast revisions					% $PRESP_{i,j,t}$ =1
		Mean	Median	Std	P25	P75	
1995	18,232	26.93	14	29.13	3	45	17.50
1996	18,698	27.05	13	30.31	2	48	22.05
1997	21,453	26.91	10.5	31.19	2	49	24.57
1998	25,336	24.42	5	31.41	1	45	34.23
1999	26,613	23.49	3	32.68	1	45	40.87
2000	25,634	24.03	3	33.07	1	48	42.57
2001	34,999	18.80	1	30.84	1	24	54.24
2002	35,211	18.52	1	31.26	1	22	58.64
2003	38,199	18.53	1	31.80	1	21	61.06
2004	44,169	16.87	1	30.92	1	11	64.40
2005	47,285	15.70	1	30.06	1	6	65.86
2006	48,817	14.81	1	29.56	1	5	67.08
2007	49,034	14.09	1	28.70	1	4	67.86
2008	52,799	11.67	1	25.69	1	4	68.48
2009	60,119	11.16	1	25.30	1	3	68.61
2010	60,610	11.70	1	26.31	1	3	68.91
2011	59,639	12.09	1	26.76	1	4	68.06
2012	58,321	11.93	1	26.56	1	4	68.79
2013	60,100	12.07	1	26.92	1	4	68.59
2014	61,393	11.66	1	26.21	0	4	67.85
2015	61,910	11.27	1	25.70	0	4	67.82
Overall	915,449	15.26	1	28.81	0	8	61.26

Table 1 Continued:

Panel B

Year	# Firm-Quarter	# of Analyst per firm		NRESP j,t		PRESPj,t		DPRESPj,t
		Mean	Median	Mean	Median	Mean	Median	Mean
1995	7,203	4.99	4	1.03	0.5	17.50	9.09	49.00
1996	7,545	5.02	4	1.28	1	22.05	12.50	55.49
1997	8,422	5.26	4	1.49	1	24.57	14.29	58.72
1998	8,618	6.13	5	2.30	1	34.24	22.22	71.90
1999	8,388	6.61	5	2.96	2	40.87	33.33	78.24
2000	7,692	7.11	6	3.37	2	52.57	33.33	78.91
2001	8,583	8.63	7	5.03	4	54.24	50.00	85.02
2002	8,991	8.12	7	5.01	4	58.64	57.14	89.22
2003	9,199	8.77	7	5.56	4	61.06	60.00	91.50
2004	9,914	9.26	8	6.15	5	64.46	66.67	93.34
2005	10,315	9.30	8	6.26	5	65.86	66.67	94.28
2006	40,421	9.13	8	6.28	5	67.08	66.67	95.23
2007	40,493	8.91	8	6.19	5	67.86	69.23	95.05
2008	11,043	9.17	9	6.42	6	68.48	71.43	95.18
2009	11,381	10.25	10	7.23	6	68.61	69.23	95.82
2010	10,627	11.30	10	8.00	7	68.90	70.00	96.51
2011	10,221	11.43	11	7.85	7	68.06	69.23	96.92
2012	9,792	11.76	11	8.17	7	68.79	71.43	97.22
2013	10,116	11.80	11	8.12	7	68.59	71.43	97.29
2014	10,503	11.59	11	7.92	7	67.85	69.57	96.86
2015	10,799	11.62	11	7.85	7	67.82	70.00	97.12
Overall	260,266	9.67	8	6.30	5	55.86	60.00	90.09

Our final data after merging I/B/E/S with CRSP, Compustat, Thomson Reuters CIG database and following standard elimination is 168,896 earnings announcements. Of this 130,006 have bundled forecasts. We calculate the earnings surprise, SUE, from the I/B/E/S data base and it is the actual minus I/B/E/S mean forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter end. It has a mean close to zero and is symmetrically distributed. We also calculate the cumulative abnormal return for the three-day window (-1, +1) centered on the earnings announcement date of the current quarter t and find it to be symmetrically distributed with a mean of zero. We use two specifications, one adjusted for size and the other for the expected returns based on the Fama French 3 factor model. CAR is the abnormal return on a stock, cumulated from one day after an earnings announcement through the next 60 trading days. The CAR-Size adjusted abnormal return is the cumulated raw return minus the average return on an equal-weighted portfolio of the NYSE/AMEX/NASDAQ firm-size decile to which the firm belongs. The CAR-3 Factor abnormal return is the cumulated raw return minus the expected return for the stock calculated from the Fama French 3 factor model. We also calculate Buy and Hold returns which are size adjusted and adjusted for the expected returns from a Fama French 3 factor model. They are denoted by BHAR-Size adjusted and BHAR-3 Factor. MV of Equity is the market cap of the firm and Price per share is the closing price. In Panel B, we include firm that have at least one analyst forecast within 1 trading day of earnings announcement (DPRESP=1). We calculate a new measure, NAFR, as the difference between change in the mean analyst annual forecast 1 day after the earnings announcement and the mean analyst annual forecast immediately before the announcement minus the earnings surprise, scaled by the stock price. Panel C shows the summary statistics for firms which did not have responsive analyst updates. We can see that the NAFR has characteristics and distribution like that of SUE. One of the differences that does show up is that firms that have bundled analyst forecast tend to be slightly larger firms on average.

TABLE 2: Descriptive Statistics of Key Variables

The Panel A includes all firm-quarters with data to calculate SUE and returns during the period Q1/1995 to Q1/2016. SUE is calculated from the I/B/E/S data base and it is the actual minus I/B/E/S mean forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter end. PRC is the cumulative abnormal return for the three-day window (-1,+1) centered on the earnings announcement date of the current quarter t. CAR is the abnormal return on a stock, cumulated from one day after an earnings announcement through the next 60 trading days. The CAR-Size adjusted abnormal return is the cumulated raw return minus the average return on an equal-weighted portfolio of the NYSE/ AMEX/ NASDAQ firm-size decile to which the firm belongs. The CAR-3 Factor abnormal return is the cumulated raw return minus the expected return for the stock calaculated from the Fama French 3 factor model. We also calculate Buy and Hold returns which are size adjusted and adjusted for the expected returns from a Fama French 3 factor model. They are denoted by BHAR-Size adjusted and BHAR-3 Factor. MV of Equity is the market cap of the firm and Price per share is the closing price. In Panel B, we include firm that have at least one analyst forecast within 1 trading day of earnings announcement (DPRESP=1). We calculate a new measure, NAFR, it is calculated as the difference between change in the mean analyst annual forecast 1 day after the earnings announcement and the mean analyst annual forecast immediately before the announcement minus the earnings surprise, scaled by the stock price.

Variable	N	Mean	Std	10th Pctl.	25th Pctl.	50th Pctl.	75th Pctl.	90th Pctl.
Panel A: All firms								
SUE	168,896	-0.001	0.018	-0.006	-0.001	0.000	0.002	0.006
PRC - Size adjusted	168,896	-0.001	0.079	-0.092	-0.038	0.000	0.039	0.091
PRC - 3 Factor	168,896	-0.001	0.080	-0.094	-0.038	0.000	0.040	0.092
CAR - Size adjusted	168,896	0.000	0.199	-0.231	-0.101	0.001	0.104	0.230
CAR -3 Factor	168,896	0.007	0.190	-0.215	-0.091	0.007	0.104	0.228
BHAR - Size adjusted	168,896	-0.002	0.193	-0.223	-0.109	-0.009	0.090	0.220
BHAR -3 Factor	168,896	0.001	0.191	-0.222	-0.103	-0.004	0.095	0.222
MV of Equity (in $mn)	168,896	5,339.2	17,565.9	128.4	292.0	867.5	2,942.5	10,358.5
Price Per Share	168,896	28.7	25.0	6.0	11.9	22.4	37.8	57.7

TABLE 2 continued

Variable	N	Mean	Std	10th Pctl.	25th Pctl.	50th Pctl.	75th Pctl.	90th Pctl.
Panel B: Bundled sub-sample								
SUE	130,006	0.000	0.015	-0.005	0.000	0.000	0.002	0.006
New Measure (NAFR)	130,006	-0.010	0.072	-0.030	-0.004	0.001	0.007	0.019
PRC - Size adjusted	130,006	0.000	0.081	-0.093	-0.039	0.001	0.042	0.095
PRC - 3 Factor	130,006	0.001	0.081	-0.094	-0.039	0.001	0.043	0.096
CAR - Size adjusted	130,006	0.005	0.186	-0.207	-0.091	0.004	0.101	0.220
CAR -3 Factor	130,006	0.010	0.178	-0.196	-0.084	0.008	0.101	0.217
BHAR - Size adjusted	130,006	-0.001	0.189	-0.214	-0.105	-0.008	0.090	0.214
BHAR -3 Factor	130,006	0.006	0.180	-0.201	-0.093	0.000	0.094	0.213
MV of Equity	130,006	6,287.5	19,185.0	158.6	374.1	1,106.3	3,679.5	12,864.4
Price Per Share	130,006	30.3	26.5	6.0	12.2	23.6	40.2	61.3

4.2. NAFR vs SUE

We compare the firm rankings based on SUE and the NAFR. We see that there is a significant correlation between the two at 52%. It is significant but not high enough to suggest that the two effects are identical. We then break down the overlap between the firms' ranking based on the deciles that they belong to. We find that the overlap between RUE and RNAFR is the highest for firms with DSUE =0 and DSUE =9, where DSUE is the decile based on SUE. The overlap for these two deciles is above 50 percent whereas for the other deciles it is much lower. This leads us to believe that the SUE PEAD effect which looks at the return on the long-short portfolio between decile 0 and decile 9 could be impacted by changes in analysts' expectations (which the NAFR tries to capture).

Table 3: Ranking by New Measure (NAFR) and Ranking by SUE
RUE is calculated from rank given to the raw unexpected earnings, SUE*j,t,*ranked into deciles indexed from 0 to 9 by quarter and then the indices are divided by 9 and subtract 0.5 to get the independent variable RUE*j,t*, which ranges between -0.5 and 0.5. Ranking for the New Measure, RNAFR, is calculated in a similar manner, we take rank given to NAFR*j.t* to create the deciles.

Correlation Coefficient (RUE, RNAFR)	52%

Decile	Firm- Quarter with Bundled Forecasts	Firm-Quarter with same RUE and RNAFR	% Overlap
0	12,122	7,145	59%
1	12,556	4,459	36%
2	14,197	3,700	26%
3	11,771	2,941	25%
4	13,740	3,631	26%
5	13,795	3,364	24%
6	13,454	3,217	24%
7	13,060	3,317	25%
8	12,877	4,171	32%
9	12,434	7,086	57%

To compare the profitability of the two strategies we create the deciles based first on RUE and then based on RNAFR. Figure 1 shows that returns from such a long short strategy. To eliminate noise, we aggregate the 10 portfolios into three groups. The Top group is the average return of deciles 7, 8, and 9. The Bottom group is the average return from deciles 0, 1, and 2. The Middle shows the average return from the remaining 4 deciles (3, 4, 5, and 6). The CAR- size adjusted from a long-short strategy is 1.73% for the 60 days which corresponds to almost 7 percent annually.

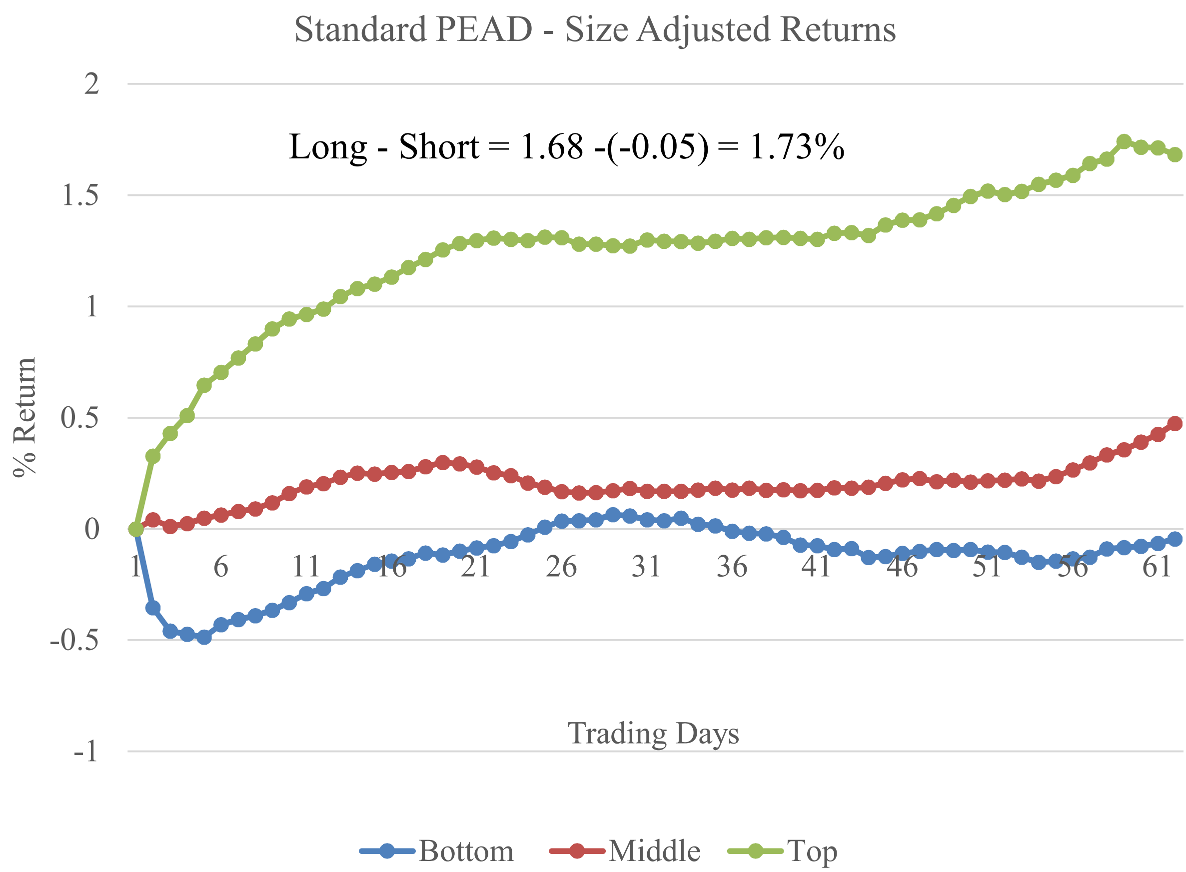

Figure 1: Size Adjusted Cumulative Returns and RUE

In this figure, we plot the size-adjusted cumulative abnormal defined as the cumulative raw return minus the average return on an equal-weighted portfolio of the NYSE/AMEX/NASDAQ firm-size decile to which the firm belongs. We plot CAR for +1 to +60 after the earnings announcement. The portfolios based on RUE (RUE is calculated from rank given to the raw unexpected earnings, SUE*j,t,* ranked into deciles indexed from 0 to 9 by quarter and then the indices are divided by 9 and subtract 0.5 to get the independent variable RUE*j,t*, which ranges between -0.5 and 0.5.) are averaged into three groups, the Top (comprises of the average of top three deciles), the Bottom (average of the bottom three deciles) and the middle (sum of the remaining four middle deciles). Trading strategy based on buying the Top and short selling the bottom over a +1, to +60 window yields a return of 1.73% which translates to 6.92% annually.

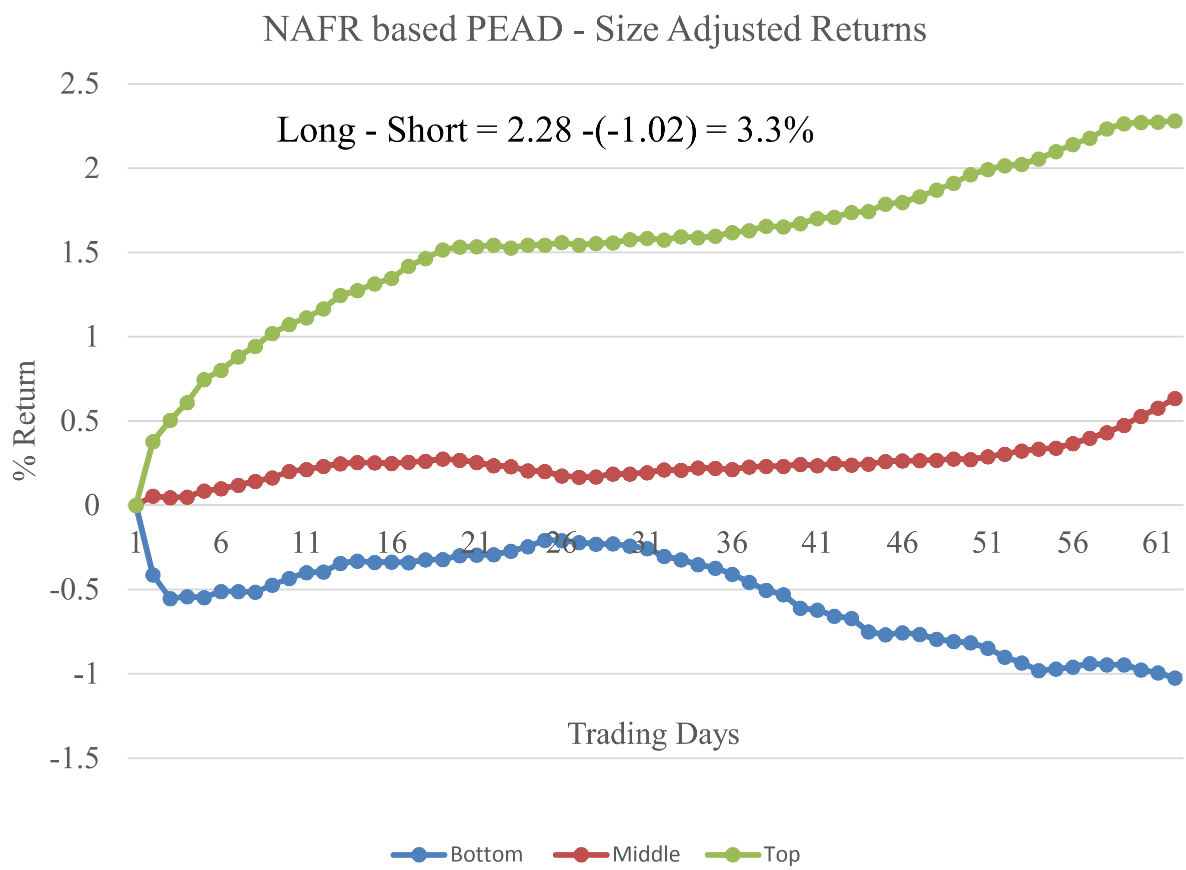

Figure 2: Size Adjusted Cumulative Returns and RNAFR

In this figure, we plot the size-adjusted cumulative abnormal defined as the cumulative raw return minus the average return on an equal-weighted portfolio of the NYSE/AMEX/NASDAQ firm-size decile to which the firm belongs. We plot CAR for +1 to +60 after the earnings announcement. The portfolios are based on RNAFR (Ranking for the New Measure, RNAFR, is calculated in a similar manner to RUE, we take rank given to NAFR$j.t$ to create the ten deciles) are averaged into three groups, the Top (comprises of the average of top three deciles), the Bottom (average of the bottom three deciles) and the middle (sum of the remaining four middle deciles). Trading strategy based on buying the Top and short selling the bottom over a +1, to +60 window yields a return of 3.30% which translates to 13.2% annually.

We compare the returns from the SUE ranked portfolios to the returns generated by the portfolios ranked on the New Measure. Again, we aggregate the deciles and use three groups.

We find that the Size – adjusted CAR generated by the long portfolio is 2.28 percent and those generated by the short portfolio is 1.02 percent. Combined this yield 3.3% over 60 trading days or close to 13 percent annual returns. Note that these are abnormal returns and we have verified the results for other adjustments as well (like the Fama French 3 factor model) and the results remain. Clearly, the strategy based on the New Measure outperforms that earning surprise based strategy by more than 6 percent annually. The results will be higher if we consider only the top and bottom portfolio as it will be visible in the regression results in the next sub-section. The returns are well above transaction cost for a long-short equity strategy.

Table 4 compares the size adjusted and Fama French 3 factor adjusted cumulative abnormal returns of portfolios formed based on SUE deciles and the NAFR deciles. A long-short position in the high minus low (10-1) portfolios based on SUE ranking gives a return of 2.7 percent both for the size adjusted cumulative abnormal returns as well as for the Fama-French 3-factor adjusted cumulative abnormal returns over the next 58 trading days. The size adjusted cumulative abnormal returns for the high minus low portfolios based on net analyst forecast revision is generates a 4.6 percent return over the same window. The samples are of different size for the SUE deciles and NAFR deciles since not all firm quarters have bundled analyst forecast. In a different specification, keeping the samples for the two identical we still find that the long short strategy based on NAFR yields far superior returns.

Table 4: Raw Portfolio Returns
The table reports portfolio returns of the stocks in our sample sorted into deciles on two different rank measures, SUE and NAFR. We report the cumulative abnormal returns, size adjusted and Fama-French 3 factor adjusted over a window starting two days after the earnings announcement and going till 60 trading days post announcement.

	SUE decile			NAFR decile		
	N	[2,60] SAR	[2,60] FF	*N*	[2,60] SAR	[2,60] FF
1	16,833	-0.001	-0.004	13,942	-0.017	-0.011
		-2.81	*-2.96*		*-6.74*	*-2.60*
2	16,881	-0.046	-0.001	12,793	-0.016	-0.010
		-3.10	*-1.02*		*-9.18*	*-5.70*
3	17,023	-0.049	-0.003	12,814	-0.012	-0.004
		-3.92	*-2.59*		*-7.94*	*-2.55*
4	15,550	0.003	0.008	12,786	-0.003	0.004
		0.25	*6.20*		*-2.28*	*3.12*
5	16,142	0.007	0.013	12,797	0.008	0.015
		5.62	*11.22*		*6.15*	*11.48*
6	16,931	0.004	0.010	12,869	0.009	0.015
		3.05	*8.43*		*6.58*	*11.64*
7	16,904	0.005	0.012	13,008	0.005	0.012
		3.84	*9.62*		*5.72*	*9.21*
8	16,895	0.006	0.008	13,008	0.108	0.015
		4.15	*8.18*		*7.31*	*10.87*
9	16,885	0.014	0.015	13,017	0.020	0.020
		9.18	*9.91*		*12.37*	*12.93*
10	16,853	0.026	0.024	12,971	0.028	0.029
		13.96	*13.39*		*15.68*	*14.97*
10-1		0.027	0.027		0.046	0.040
		12.24	*10.78*		*15.89*	*14.50*

4.3. PEAD and bundled analyst forecasts

We next test the effect of bundled forecast on the standard PEAD. Our left-hand side variable is the CAR adjusted either for size or the 3 factor Fama French model. The main independent variable is RUE, its coefficient gives the amount of return from the long short trading strategy. We include a dummy variable DPRESP which equals 1 if there is a bundled forecast for the firm j in quarter t. To find whether a bundled forecast increases or decreases the PEAD we add an interaction term between RUE and DPRESP. If bundled forecast reduces PEAD, which is our prior, then we expect the co-efficient of the interaction term to be negative. The co-efficient of RUE and the return from the long-short strategy is 3.7 percent for the size adjusted CAR and 3.3 for the Fama French 3 factor adjusted CAR. If we compare these to previous studies like Zhang (2008), we do find evidence of reduction in PEAD. Zhang (2008) had size adjusted returns of 5.2 percent and Livant and Mendenhall (2006) had PEAD of 4.91 percent. Both the studies had data which ended before 2003.

The interaction term is negative, in line with our priors. However, the magnitude is only 0.2 percent implying that bundled forecast reduces drift by 0.2 percent. Next, we add controls to the mix and the direction of the interaction term holds the appropriate sign. Also adding the controls increases the overall R-squared of the model.

Table 5: Post Earning Announcement drift and analyst responsiveness

The table shows the regression results for the CAR as the dependent variable. Independent variables include RUE, DPRESP, the interaction between DPRESP and RUE and control variables like Log of market capitalization, a dummy variable called Guide which equals 1 if the firm provides EPS guidance, 0 otherwise. COV, is the number of analysts covering the firm. BNEWS is a dummy variable which equal 1 if the firm had negative surprise. Q4 is an indicator variable which equals 1 if the quarter is the fourth quarter. We also have year fixed effects included in the regressions. Model 1 does not include the control variables and their interaction terms, whereas Model 1(a) does.

	Model 1				Model 1(a)			
	Size Adjusted CAR [+1, +60]		FF 3Factor Adjusted CAR [1+, +60]		Size Adjusted CAR [+1, +60]		FF 3Factor Adjusted CAR [1+, +60]	
	Co-efficient	t-value	Co-efficient	t-value	Co-efficient	t-value	Co-efficient	t-value
Year Fixed effect	*Yes*		*Yes*		*Yes*		*Yes*	
RUE	0.037	13.10	0.033	12.02	0.011	4.93	0.054	2.46
DPRESP*RUE	-0.020	-6.05	-0.020	-6.38	-0.013	-3.61	-0.013	-3.86
DPRESP	-0.001	-1.21	-0.004	-3.29	-0.001	-1.03	-0.022	-1.85
LOGMV*RUE					-0.002	-1.61	-0.001	-0.06
GUIDE*RUE					-0.002	-5.56	-0.002	-6.09
COV*RUE					0.000	0.00	0.000	0.00
BNEWS*RUE					-0.147	-17.28	-0.074	-9.13
Q4*RUE					-0.015	-4.46	-0.011	-3.44
LOGMV					0.016	44.13	0.012	33.59
GUIDE					-0.009	-6.63	-0.008	-5.98
COV					-0.004	-31.19	-0.003	-27.77
BNEWS					-0.034	-11.05	-0.018	-6.00
Q4					0.005	4.89	0.008	8.00
N	168,896		168,896		168,896		168,896	
R Squared	0.005		0.007		0.017		0.0154	

4.4. PEAD and the new measure

Finally, we want to examine how the new measure performs compared to the standard measure based on earnings surprises. To ascertain the explanatory power of the SUE and NAFR we run a double sort where we allocate stocks first based on NAFR to deciles. Then for each decile thus created we rank stocks based on SUE and form 10 more deciles for each of the NAFR deciles. The results are presented in table 6 and they show that while there NAFR rank based deciles show profitable portfolios for a long-short strategy, clear results do not appear when looking at the SUE rankings. High minus low CAR based on size adjusted return for decile 1 is 4.3 percent and is significant, whereas the high minus low for SUE decile 1 is -1.5 percent and in not significant. For decile 10 based on NAFR and high minus low strategy yields 4.7 percent returns whereas the decile 10 for SUE based yields a negative 1.3 percent return. This implies that the results we have are largely driven by the NAFR measure and not the SUE measure. We also run independent sorts and the results not reported in the paper for brevity yield similar results.

Table 6: Double Sort
The table reports the results from double sorting our sample by ranks based on NAFR and SUE. The portfolio returns are size adjusted cumulative abnormal returns starting from two trading days after earnings announcement till 60 trading days following the announcement.

		NAFR decile										High NAFR-Low NAFR	
		1 (Low NAFR)	2	3	4	5	6	7	8	9	10 (High NAFR)		
SUE decile	1 (Low SUE)	0.001	0.000	0.009	0.008	0.004	0.016	0.012	0.009	0.014	0.044	**0.043**	*4.33*
	2	-0.016	-0.001	-0.003	-0.003	0.010	0.020	0.010	0.014	0.013	0.031	**0.047**	*4.98*
	3	-0.012	-0.007	-0.013	-0.001	0.017	0.007	0.010	0.006	0.028	0.033	**0.044**	*5.12*
	4	-0.011	-0.015	-0.011	0.001	0.011	0.023	0.006	0.017	0.010	0.027	**0.038**	*4.39*
	5	-0.014	-0.020	-0.011	0.000	0.016	0.011	0.007	0.012	0.019	0.029	**0.043**	*5.12*
	6	-0.013	-0.018	-0.018	-0.006	0.012	0.017	0.014	0.015	0.023	0.032	**0.044**	*5.28*
	7	-0.010	-0.026	-0.021	-0.005	0.009	0.001	0.013	0.010	0.028	0.036	**0.046**	*5.88*
	8	-0.012	-0.039	-0.023	-0.007	0.005	-0.005	0.010	0.009	0.029	0.042	**0.054**	*6.14*
	9	-0.003	-0.023	-0.011	-0.015	-0.002	0.001	0.003	0.010	0.015	0.036	**0.039**	*4.47*
	10 (High SUE)	-0.015	-0.016	-0.019	-0.007	-0.006	-0.010	0.004	0.005	0.024	0.031	**0.047**	*4.10*
High SUE-Low SUE		-0.015	-0.015	**-0.028**	**-0.016**	-0.010	**-0.025**	-0.007	-0.004	0.010	-0.013		
		-1.48	*-1.72*	*-3.62*	*-2.17*	*-1.49*	*-3.67*	*-1.08*	*-0.57*	*1.260*	*-1.23*		

To confirm the analysis in Table 6 we run regressions, where we add ranks based on both measures as explanatory variables for the PEAD and the results indicate that the ranking based on new measure explains most of the PEAD. The return generated by the long-short based on ranking of the new measure is 4.6 percent compared to the SUE based portfolios only explaining 0.5 percent.

In a model where we add the various controls we see that the RUE is no longer significant. Implying that the explanation power of RUE stems from having RNAFR based stocks in its portfolios. RUE does not have any explanatory power over the new measure. And as we have shown in the figures 1 and 2. The profits generated from RNAFR portfolios are far greater than the profits generated by RUE portfolios.

4.5. Robustness tests

In this subsection, we show that our inferences about the explanatory power of RNAFR over RUE is robust to various specifications.

4.5.1. PEAD as BHAR

We repeat all our analyses by replacing the CAR adjusted for size and the market models with buy and hold returns adjusted for the size and the market model and find that our results hold. BHAR based on RUE does not yield explanatory power in the presence of RNAFR.

Table 7: Post Earnings Announcement Drift based on the new measure

In this table we run regression with CAR as the dependent variable and the RNAFR and RUE as the independent variables. In model 2, the dependent variable is the Size Adjusted CAR, whereas in Model 2(a), the dependent variable is the Fama French 3 Factor adjusted CAR. In Model 3, we add the control variables, but remove RUE and Model 4 contains all the regressors.

	Model 2		Model 2(a)		Model 3		Model 4	
	Size Adjusted CAR [+1, +60]		FF 3Factor Adjusted CAR [1+, +60]		Size Adjusted CAR [+1, +60]		Size Adjusted CAR [+1, +60]	
	Co-efficient	t-value	Co-efficient	t-value	Co-efficient	t-value	Co-efficient	t-value
Year Fixed effect	*Yes*		*Yes*		*Yes*		*Yes*	
RNAFR	0.046	23.82	0.039	20.96	0.016	6.67	0.016	6.65
RUE	-0.009	-4.76	-0.010	-5.26			-0.002	-0.05
LOGMV*RNAFR					-0.005	-3.87	-0.005	-3.86
GUIDE*RNAFR					-0.002	-4.63	-0.002	-4.63
COV*RNAFR					0.000	0.00	0.000	0.00
BNEWS*RNAFR					-0.031	-7.95	-0.031	-7.89
Q4*RNAFR					-0.007	-1.83	-0.007	-1.83
LOGMV					0.014	35.78	0.014	35.31
GUIDE					-0.009	-6.44	-0.009	-6.44
COV					-0.003	-27.14	-0.003	-27.10
BNEWS					0.005	3.51	0.005	2.31
Q4					0.004	3.12	0.004	3.12
N	130,006		130,006		130,006		130,006	
R Squared	0.008		0.011		0.019		0.019	

5. Conclusions

We create a new measure which measures the change in expectations to explain the PEAD and show that it significantly outperforms the earnings surprise based measures. The superiority of the new measure stems from its ability in capturing the announcement accurately and being able to predict the direction information production related to the firm in the future. We use update in annual eps forecast by analyst adjusted for the current surprise, standardized by the stock price as the new measure. We show that the returns generated by the standard earnings based PEAD could be driven by the fact that the bottom and the top decile of the SUE based PEAD have a high overlap with the firm ranked based on the new measure. If both measures are used simultaneously to explain PEAD, then the earnings surprise based measure loses its explanatory power. Our results show that PEAD results from information production and the drift observed in prices is a movement towards the changes in expectations and not an under-reaction or delayed response to the earnings announcement.

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Chapter 3

Delayed disclosures and institutional trading

Abstract

The following study reconciles the conflicting results of the studies on institutional trading around corporate events. Several low-frequency studies show that connected institutions trade profitably around corporate events like analyst revisions, mergers, SEOs, debt refinancing, etc. Griffin, Shu and Topaloglu (2012) using broker level trade executions show that institutional investors do not take advantage of information leakages. We use delayed disclosure as a setting that creates informational advantages and find that connected brokers do trade profitably around such events.

1. Introduction

Institutional Investing has been widely studied by finance academics. The current study is an attempt to resolve the conflicted understanding among academics on whether institutional investors take advantage of their access to private information by trading on such information? Griffin, Shu and Topaloglu (2012) henceforth GST, challenges the prior belief that institutions were taking advantage of private information. They suggest that institutional investors do not take advantage of the information they might have access to, through their connections, to benefit in the short term. The research finds itself contradicting studies like that by Hendershott, Livdan and Schürhoff (2015) that shows that institutional net trades around corporate events not only predict the sentiment of the news but also the market's reaction to the event. Their findings support previous findings of several studies including those by Bodnaruk, Massa, and Simonov (2009), Jegadeesh and Tang (2010), Massa and Rehman (2008), Ivashina and Sun (2011), Irvine, Lipson, and Puckett (2007), and Acharya and Johnson (2010) among others.

We use delayed disclosure as a setting for the possible information leakages. We look at all 8-K announcements made by firms, a disclosure is delayed if there is a gap between the occurrence of an event and the filing of the same with the SEC. The SEC allows firms with up to 4 business days to report corporate events. Study by Wu and Goldstein (2015) shows that information asymmetry increases during such delays. Ben-Rephael, Da, Easton and Israelsen show that institutional investors are informed about event date of 8-K announcements and that several 8-K filings contain "stale" news. In addition to our focus on events with delayed disclosures we analyze institutional trading using transaction-level data provided by Abel Noser. The data covers between 12 and 15 percent of CRSP volume and has been used in over 50 publications till date.

2. Data and research methodology

Our trading data comes from Abel Noser, a transaction cost analysis company, and contains self-reported trades made by institutions who are identified by a client code. The data also has codes to identify the manager and the broker. The broker and manager reference files are available only for a sub sample of the Abel Noser data and hence we are restricted to only two years, 2007 and 2008. The data contains close to 7 million tickets, executed by 488 brokers, servicing 939 funds. We designate each client-manager pair as a fund and map its trading relationship with a broker. Next, we rank the relationship between a fund and their broker into three groups based on two criteria: the trade volume executed and the commissions paid for the executions. Thus, for each fund we rank the brokers it uses in to three groups based on volume and commissions and for each broker we rank the funds that they service into three groups which gives rise to a three by three matrix where (0,0) represents trades that are executed by funds through their top brokers and these funds are also the brokers best clients.

For events we use SEC's edgar database to collect all 8-K filings and we calculate the delay between the event date and the filing date. We have 49,499 such filings with an average delay of 2.82 days.

3. Empirical Results

For our first analysis we look at the performance of trades executed by institutional clients based on their relationship with brokerage house and we see that bulk of the trades happen between brokers and clients that have strong relationships. However, these trades on average are not profitable. Trades executed by institutional investors through brokers with whom they do not share a strong relationship and trade seldom, are the ones that seem to perform better on average. The implication points to the institutional investors either hiding his trading from his main brokers. This possible reason this could arise is due to the investor either the investor does not want the main broker to have that information. He is avoiding being front-run or is simply hiding his identity from the markets. The other reason could be that he does not want to trade via the broker that has provided him with the information.

4. Conclusion

We find that institutional investors trades are profitable when they are not executed through their main broker. This provides an explanation why Griffin et al. (2012) are unable to find informed trading by institutional clients when they observe trades executed by informed brokers. The study reconciles the literature on informed trading by institutional investors.

Table 1: Abnormal Returns and relationship.
Computes 1-day abnormal returns for trades executed by institutional investors in the Abel Noser database for years 2007 and 2008. All funds have been grouped into 3 groups based on the volume of their business and commissions paid. With zero being the highest trading and 2 being the least. Similarly, brokers have been ranked into three groups based on the amount of business they receive from institutions with zero being the highest and 2 being the least. A ticket is sum of the trades executed by a broker for the fund on a given stock on a given day.

Panel A: Ranked on Volume

		Returns			# of Tickets in each group		
		Fund			**Fund**		
		0	1	2	0	1	2
Broker	0	**0.060**	**0.147**	**0.081**	5,946,015	656,930	99,894
	1	**0.151**	**0.291**	0.020	317,585	121,329	35,905
	2	**0.255**	**0.213**	**0.265**	23,600	32,512	18,884

Table 1 continued:
Panel B: Ranked on Commission

		Returns			# of Tickets in each group		
		Fund			**Fund**		
		0	1	2	0	1	2
Broker	0	**0.063**	**0.128**	**0.079**	6,011,562	644,184	97,922
	1	**0.143**	**0.302**	0.005	290,759	113,278	26,642
	2	**0.239**	**0.209**	**0.332**	23,267	27,954	17,086

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