Asymmetry in the Impact of Institutional Trades

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Abstract

Permanent price impact reflects the information content of institutional trades and gauges the superiority of institutional research. Price impact differs for buys and sells; the asymmetry between the two has been shown to be positive. However, we show that the direction of the asymmetry depends on the constraints related to capital, diversification, and short-selling. The sign of the permanent price impact asymmetry 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. Other determinants include idiosyncratic volatility, analyst forecast dispersion, trading intensity and price dispersion.

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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. 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 price impact is affected by the proportion of informed trading by institutions in the market, as not all of whom may trade at all times due to various constraints. Studies by Holthausen, Leftwich, and Mayers (1987, 1990); Keim and Madhavan (1995 and 1997); and Chan and Lakonishok (1993, 1995) all report that the price impact 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.[1]

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) 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

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

to short sell when they do not initially hold the stock;[2] (b) institutions are limited in their ability to borrow to invest, and thus face a capital constraint when buying; and (c) institutions need to diversify their investments and are reluctant to add to positions in which they already have significant exposure. The capital and diversification constraints may also trigger portfolio rebalancing activities that may go against and dampen the exploitation of price sensitive information by institutions. Given these conditions, the history of stock price performance asymmetrically influences how institutions trade in order to benefit from their information and analysis. In turn, the trading patterns asymmetrically affect the proportion of informed buy and sell orders in the market, resulting in asymmetric price impacts on institutional buys and sells. As an example, using trade data from the Australian Stock Exchange, Yang (2011) shows that buyer initiated trades increase the ask price more than the bid price, and seller initiated trades decrease the bid price more than the ask price. Our focus is on trade prices. 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. This is due to a change in the institutional constraints, as described in more detail in the next section. Furthermore, the asymmetry might even be negative if the price run-up history is long enough. To the best of our knowledge, the results of these theoretical predictions have not been tested empirically.

Our key contributions to the literature are as follows. First, our results are intuitive, but new, and represent the first empirical test of the leading theoretical model (Saar, 2001) which highlights the importance of stock price history in gauging the information content of institutional trades under varying constraints. Second, we empirically expand the theoretical list of

[2] 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)).

determinants of permanent price impact by investigating various informational variables such as idiosyncratic volatility; analyst forecast dispersion, trading intensity, and stock price dispersion. Third, we employ an experimental design where we have an institutional trading treatment group and a no institutional trade (NIT) control group, thus ensuring that our price impact measure is robust and reflects the pure effects of institutional trades devoid of the effects of risk and other systematic factors. This approach also rules out the possibility that our results are driven by price patterns unrelated to institutional trades. Fourth, we introduce a novel method to calculate the permanent price impact of institutional trades in a time when order splitting is a pervasive tool for minimizing total price impact. Many previous studies have assumed that institutional investors' trades could be easily identified from large trade sizes exceeding 10,000 shares (Madhavan and Cheng, 1997) or by dollar volume traded above a certain amount (Lee and Radhakrishna, 2000; and Hvidkjaer, 2006). Chakravarty (2001) and Ascioglu, Comerton-Forde and McInish (2011) point out that informed institutions engage in stealth trading by splitting their large orders into much smaller trades and as a result medium or small sized trades tend to move prices more. In recent institutional trade datasets, we find that institutions use multiple small trades on the same stock on the same day and some of their strategies generate both buys and sells. Thus, a relevant measure of institutional trade flow in the current environment is the institutional buy minus institutional sell trade flow aggregated for a given stock on a given day. This measure helps us capture institutional price impact more accurately than findings reported in studies that compute price impact at trade level and include trades of large sizes only.

Our findings provide empirical evidence on the controversial issue of asymmetry in the permanent price impact of institutional trades. This issue has been identified as an important question for further research (Chan & Lakonishok, 1993, p.197) and described as both 'intriguing'

(Holthausen et al., 1987, p.90, and Chan & Lakonishok, 1993, p.175) and a 'key puzzle' (Chan & Lakonishok, 1993, p.197). Our results are expected to have implications for institutional players, given that price impact is described as 'indeed the main driver of total costs of institutional trading' (Chiyachantana, Jain, Jiang, and Wood, 2004, hereafter CJJW, p.896).

The primary findings presented in this article may be summarized as follows. Price impact asymmetry varies significantly based on the history of stock price, informational variables, 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. Figure 1 displays the reduction in asymmetry in price impact with the increase in the price run- ups. At the beginning of a price run the market adjusted price impact is 89 bps for a buy and 37 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. Moreover, 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 constrained ability of institutions 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, trade size, and contemporaneous market condition. Our work is closely related to an extensive and growing literature on the relationship between institutional trading

activity and stock prices. Our results differ from previous studies claiming that institutional buys are more informative. In contrast, we show that institutional buys are not always more informative than sells. Instead, the information content of institutional trades and the resulting abnormal returns vary with a stock's price history and firm-specific information characteristics - both of which affect various institutional constraints related to capital, diversification, and short selling.

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 mutual funds under varying circumstances.

1. Literature Review and Research Hypotheses

We begin with the definition of price impact commonly used in the literature, with particular 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). This total price impact can be decomposed into 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 change give rise to a new equilibrium price level that

sustains well after the institutional trade is completed. The permanent price impact is thus calculated 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 the trades initiated by informed traders. The focus of our study is on the permanent price impact asymmetry that relates to informational issues.

The literature on whether institutions are informed is controversial. Fama (1991), Lakonishok, Shleifer and Vishny (1992) and more recently Barras, Scaillet and Wermers (2010) posit that professional investors do not display superior performance relative to the market. We believe that this finding, implying a lack of information content in institutional trades, is a result of aggregating all stocks and all institutions. In contrast, one needs to look at specific dimensions of stock characteristics and market conditions overlooked in the prior literature. Boehmer and Kelley (2009) show that stocks with greater institutional ownership are more informationally efficient and institutional trading activity drives the informational efficiency in prices. It is possible to identify situations that offer exploitable informational advantage to the institutions. Indeed, Puckett and Yan (2011) suggest that interim trading skills contribute between 20 and 26 basis points per year to the average fund's abnormal performance. They claim that any trading skills documented by previous studies that use quarterly data are biased downwards because of their inability to account for interim trades. A recent study by Hendershott, Livdan and Schürhoff (2015) finds that institutional trading volume is informed and can predict news announcements, the sentiment of the news (good or bad), and the stock market reaction to the news. We believe that this information content in institutional trades manifests in the price impact of trades. Studies by Holthausen, Leftwich, and Mayers (1987, 1990), Keim and Madhavan (1995, 1997), Engel and

Patton (2004), and Chan and Lakonishok (1993, 1995) all report that the information content of institutional buys is higher than that of institutional sells. Relatively few studies find that the price impact of sell orders can be greater than that of buy orders. Exceptions include Brennan, Chordia and Subhramanyam (2012) who compute buy and sell lambdas (a proxy for price impact) and 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. Unlike Brennan, Chordia and Subhramanyam (2012) and Jondeau, Lahaya and Rockinger (2015), the focus of our paper is on institutional investors and the information content in their trades and not the intraday price movements of the overall market.

The main reasons cited for the positive asymmetry in price impact of institutional trades revolve around liquidity costs, inelastic demand curves and information effects. Liquidity costs have a temporary impact and when considering the permanent price impact they should not have an effect. As for the inelasticity of demand curves giving rise to the positive asymmetry, we believe that there is no reason why for the same stock in the secondary market, the elasticity of demand and supply should be different (as both are driven by the availability of substitutes). This leaves us with the information effects giving rise to the asymmetry.

We test the theoretical model of Saar (2001) which 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 not delay in exploiting all of their decaying information, 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, we expect more buyers to become interested in the stock. In sequential trading, this causes a rapid increase in price levels in response to buy orders at the beginning of the price run-up. However, after a few days of the 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 institutions 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:

Hypothesis1: The asymmetry in information content reflected in the permanent price impact asymmetry (difference) between institutional buys vs. 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. Stocks with a lower degree of information asymmetry do not lend themselves easily to information-based trading. In contrast, other stocks may offer institutions an opportunity to gain a substantial information advantage through research. Institutions can take advantage of this information when trading stocks with a high degree of information asymmetry. 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.

Past literature points us to several measures of the degree of information asymmetry for individual stocks, namely, 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), namely, 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 if asymmetry and its reduction as described in our first hypothesis 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 our first hypothesis.

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.

2. Data Sources and Research Design

2.1. Data

We obtain proprietary institutional trading data from the Ancerno Corporation (formerly, Abel Noser). Ancerno provides consulting and advisory services to close to a thousand domestic

institutional clients representing Eight to Ten percent of institutional trading in 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 Ancerno dataset collectively transacted over $20 trillion during our sample period of 2001-2012. We merge our dataset and the CRSP dataset to obtain 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.

2.2 Measures of Permanent Price Impact

Due to the increase in the overall trading in the markets and in particular, in institutional order flow, it has become difficult to study the price impact in the traditional sense. In most of our data we observe both Buy and Sell orders for the same stock on the same day and many 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. Also with Reg NMS and market fragmentation reducing the average size of an order, it does not make sense to drop smaller split trades from our study and assume that there is little or no information in them. Hence we devise a new measure which

[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.

accounts for multiple buy and sell orders on the same stock on a given day as well as the splitting of trades.

One of the main channels through which information diffuses into prices is due to the activities of the market maker. Consider the market maker in the Glosten and Harris (1988) model.

$$m_t = m_{t-1} + D_t [\Psi + \lambda V_t] + y_t \quad (1)$$

Where Ψ and λ are the fixed and variable permanent price impact costs, respectively. The equation describes the innovation in the conditional expectation of the security value through new information, both private (D_t ,V_t) and public (y_t).

Basically the market maker updates his expectation of the prices from m_{t-1} to m_t based on the order flow. The permanent price impact is nothing but the aggregation of the adverse selection costs of the market maker. Thus on a given day if the markets are balanced, the market maker has matching buys for sells, then the Permanent Price Impact should be low compared to days where the market is one sided. The main takeaways from the above model are that we need to consider the net imbalance between buy and sell trades to the market maker and not the orders. In a similar vein the market maker who does not know trades are part of a bigger order or from a single order treats them the same. Hence we decide to keep our study to the smallest unit, the trades, and focus on the net institutional imbalance and its direction since the aggregate imbalances determine the permanent price impact.

The changes in the market structure post decimalization and Reg NMS have been significant. Order splitting by institutional investors has become a norm. The choice of splitting orders could be part of an active VWAP strategy to reduce slippage or at times simply the need for executing owing to the presence of several small orders on top of the limit order book. We think that it will be misleading to suggest that the split orders do not carry any information. In fact the

stealth trading literature suggests that small and medium size trades are informative (Barclay and Warner, 1993). Hence we drop all trade size restrictions and consider all Ancerno institutional trades in our data.

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 (+1 or -1) 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 buy imbalance and sell imbalance.

$$\text{Raw Price Impact, PI } t+n = \left(\frac{P_{t+n}}{P_{t-1}} - 1\right) * 100 * Direction \qquad (2)$$

Where P_{t+n} is the closing price n periods after the trading day and P_{t-1} is the closing price on the day before that trade is placed. Direction is an indicator variable equal to +1 for buy institutional imbalance and −1 for sell institutional imbalance, and n takes on the values of 1, 5, or 10 days in the reported results. Our 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 abnormal returns 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 concern that pre and post trade measures of price impact are influenced by market movements which gives 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:

$$PPI_{t+n} = \left\{\left(\frac{P_{t+n}}{P_{t-1}} - 1\right) - Benchmark\ return\right\} * 100 * Direction \quad (3)$$

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. Our conclusions about asymmetry and its reduction in the presence of run ups are same for all windows. Benchmark returns are computed in two alternative ways. For market-return adjusted PPI, benchmark return is simply ($MI_{t+n}/MI_{t-1} - 1$). For beta adjusted PPI, benchmark return is defined as β_i * ($MI_{t+n}/MI_{t-1} - 1$), where β_i is estimated using return data from 1996-2012, and MI_{t+n} and MI_{t-1} are CRSP value weighted index levels on dates $t+n$ and t-1, respectively.

2.3 Controlling for Price Patterns

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. Every trading day we form a control group consisting of stocks which were not traded by institutions on that day, and the treatment group contains the stocks in our sample that were traded by institutions. The control and the sample are then further divided into price run up groups based on their prior price patterns. The differences enable us to capture the pure price impact of institutional trades without any price patterns.

We now elaborate 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. Price run-up is defined as the number of days of consecutive positive market adjusted daily returns in the stock just prior to the arrival of institutional orders. We form three distinct price history groups based on number of days in a price run-up. We then proceed to compute the price impact for both the treatment and the control 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 control stocks. The NIT (No institutional trade) adjusted Price Impact is thus defined as:

NIT adjusted PPI (NPPI) = *Raw PPIt – Control PPI* (4)

2.3. Trade Size and Permanent Price Impact

Price impact calculated for individual stock days in the previous section 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 transaction sizes of buys and sells will systematically affect our results. Thus, we calculate net trade flow weighted permanent price impact for each price history group g at $t+n$, $PPI(g)_{t+n}$, as follows:

$$PPI(g)_{t+n} = \sum_{i=1}^{m} \frac{SV_i}{\sum_{i=1}^{m} SV_i} PPI_{t+n} \quad (5)$$

Here SV_i is the Net Trade Flow for a given stock i, and it is summed over all stock days in a given group. Throughout the paper, we report this net volume weighted average permanent price impact.[5]

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

$$PIA\ (g)_{t+n} = PPI(g)_{t+n}^{Buy} - PPI(g)_{t+n}^{Sell} \tag{6}$$

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

3. Empirical Results

3.1. Summary Statistics

Following the literature on trade flow imbalance we construct a method of classifying trades into buys and sells based on the net trading flow by all institutions. This allows us to consider all orders; even the ones that are split into smaller trades. By doing this, we overcome the issues associated with multiple buy and sell orders on the same day for a given stock. For a given stock on a given day if the net trading volume by all institutional investors is positive (negative), then we call that a buy (sell) trade. Table 1 provides the descriptive statistics. Panel A has firm level characteristics. We have 4,799 securities in our final sample with average market capitalization of $2.99 billion. The total market capitalization across all the stocks in our sample is $13.94 trillion.

[5] In our robustness section, instead of *SV* as weights, we use net dollar volume *(DV)* as weights to compute dollar size weighted price impact, average transaction volumes (*TV*) as weights to compute 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.

The average volume weighted trade price is $27.98, and the average daily trading volume per stock is 8.89 million shares.

Our sample comprises 42.84 million institutional trades of all sizes. After aggregating stocks based on net institutional imbalances we have 7.29 million stock days. Of these, 3.57 million represent price run-up days and the rest are run-downs or no change. Overall institutions appear to be net buyers with the number of stock days with net buying volume equaling 3.94 million compared to 3.33 million net selling volume. On a given day we have an average of 2,416 stocks being traded in our sample.

Panel C of Table 1 reports the stocks which form part of the control group. There are on average 1,989 stocks in the Control sample on a given day with an average market capitalization of $2.21 billion. The volume weighted stock price of the control sample is $18.63 which implies that the control group does not comprise 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 reversal trends unrelated to institutional trading.

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 3 factor model for each stock each month. Its mean is 11.80%. 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 2.18%. 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 2.01 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 37.02%. All the above variables are available at monthly frequencies. Idiosyncratic volatility is calculated on a rolling window with the latest 5 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 also calculated monthly from price information on the most recent 90 days.

[Insert Table 1 about here]

3.2. Price Impact Asymmetry

The measure 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 previous 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 one day to 10 days ahead. For the raw price impact for one day we find the asymmetry to be 0.19 and this increase to 0.97 for the permanent price impact asymmetry calculated for 10 days. Our market adjusted and risk adjusted results are 0.19 and 0.15 for the one day price impact asymmetry and 0.60 and 0.43 for the 10 day price impact asymmetry respectively.

[Insert Table 2 about here]

3.3. Price Impact Asymmetry and Past Price Movement

We proceed to test our main hypothesis on how institutional constraints captured in price history affects price impact asymmetry (Saar, 2001). 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 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. 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). Within each main column, we have sub-columns for the price impact of buys, the price impact of sells, and the asymmetry between those two.

For PPI t+1, price impact of buy (sell) orders is a decreasing (increasing) function of the length of a price run-up. Buy orders arriving at 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% 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 55 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 capital and diversification constraint become more binding as we move from the early to the later stages of a price run-up. At this stage 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 our first hypothesis, 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 selling constraints that institutional investors face becomes less binding. The price impact is at 37 bps after 1-day price run-up and it increases to 46 bps for sells in stocks with 6-10 days of

consecutive price increases. This is an indication that informed selling is less constrained after a long price run-up and generates superior risk-adjusted returns.

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 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 negative at -42 bps and is statistically significant at the 5% level, which is consistent with our hypothesis 1.

[Insert Table 3 about here]

The relationship 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. 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 increase from +1 day to +10 days.

Our results extend the conventional wisdom of Keim and Madhavan (1995) and Chan and Lakonishok (1993) who 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 day 4 and day 6 of the price run-ups that the price impact for buy imbalances becomes less than the price impact for sell imbalances and keeps decreasing. The reason for restricting to 10 days is that the sample reduces significantly if we consider longer run-ups.

[Insert Figure 1 about here]

We also examine our first hypothesis 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. Interestingly, institutions tends to sell when market is going down, which leads to price impact of sells after market or beta adjustments to be higher than the raw price impact.

Lastly, we report our NIT (No institutional Trade) adjusted permanent price impact in Panel D of Table 3. Our no-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 values from the raw values. These are stocks that have undergone similar price patterns (witnessed the same number of days of price run-up), 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 PPI asymmetry results consistent with our first hypothesis. Thus, our findings of changing PPI 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.

3.4. 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 median estimates of information asymmetry for this univariate analysis. Later, we also conduct multivariate regression analysis using the actual values of these variables for each stock day.

3.4.1. Price Impact Asymmetry and Idiosyncratic Volatility (IVOL)

Panel A1 of Table 4 reports price impact asymmetry based on idiosyncratic volatility and price history. First, price impact asymmetry monotonically decreases as a price run-up becomes longer for both high and low IVOL groups which are consistent with our first hypothesis 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 our hypothesis 2a.

[Insert Table 4 about here]

3.4.2. 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[6]. We define analyst forecast dispersion as the standard deviation of the earnings forecast scaled by the share price. We divide our sample into high and low information asymmetry groups based on the median value of the analyst forecast dispersion.

Results on the relation between permanent price impact asymmetry, analyst forecast dispersion, and price history are reported in Panel A2 of Table 4. We see strong support for Saar's 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 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 67 bps for stocks with higher forecast dispersions, versus only 38 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 sell price impact and is consistent with the hypothesized reduction in asymmetry. Also consistent with hypothesis 2a, the reduction in asymmetry is more pronounced at – 63 bps for high analyst forecast dispersion stocks than the -42 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).

[6] 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).

3.4.3. Price Impact Asymmetry and Trading Intensity

In Panel B 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 our hypothesis 2b. The difference row represents the reduction in price impact asymmetry. Consistent with our hypothesis, the difference in asymmetry before vs. after a price run-up is more extreme at -52 bps for high intensity stocks than the -47 bps for low intensity stocks using the *t*+1 post-trade price benchmark.

3.4.4. Price Impact Asymmetry and Stock Price Dispersion

Our hypothesis 2b also posits 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 opposite when stocks have had extended price run-ups. The results reported in the last panel 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 (89 bps) than for low price dispersion stocks (7 bps) and the difference between the two is positive and statistically significant at 82 bps. The difference in price impact asymmetry between high and low volatility stocks narrows with 82 bps for a run-up of 1 day to 53 bps for a run-up of 6 to 10 days. The difference row shows that the price impact asymmetry reduction is more pronounced at -73 bps for high volatility stocks than 44 bps for low volatility stocks using the *t*+1 post-trade price benchmark.

3.5. Multivariate Regression of Permanent Price Impact

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

$$NPPI_{t+n} = \beta_0 + \beta_1 \, Buy\ Dummy + \beta_2 \ Price\ History + \beta_3 \, Analyst\ Dispersion + \beta_4 \ (Buy\ Dumy * Price\ History) + \beta_5 \ (Buy\ Dummy * Analyst\ Dispersion) + \beta_6 \, (Buy\ Dummy * Analyst\ Dispersion * Price\ History) + \beta_7 \, Firm\ Size + \beta_8 \, Market\ Condition + \beta_9 \, Inverse\ of\ Stock\ Price \quad (7)$$

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, 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. The use of a buy imbalance dummy allows studying the marginal impact that a buy imbalance has over the sell imbalance and thereby inferring the asymmetry from the same regression. We interact the buy imbalance dummy with price history and we find that the coefficient to be negative -0.075. This means that as price history increases the price impact of buy imbalance will fall, which is consistent with hypothesis 1. We also interact the buy imbalance dummy with the price history and analyst dispersion to test our hypothesis 2. The coefficient of the interaction positive and significant which is consistent with our hypothesis; however the interaction effect is quite small. We also include several control variables such as market condition, firm size and inverse of stock price

based on the findings in related papers on institutional trading. For example, Chiyachantana, Jain, Jiang, and Wood (2004) posit that contemporaneous market condition is an important determinant of total price impact asymmetry. We capture market condition with the monthly CRSP value weighted index return. 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. 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 tall these factors as control variables in our analysis.

The initial asymmetry is positive (assume zero price history and zero analyst dispersion) and is the difference between 0.78 (0.263+0.522) – 0.26 (0.263+0). As price history increases the difference in the price impacts and the asymmetry reduces. The coefficients imply 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. The coefficient of price history when buy dummy is 1 works out to be -0.068 (-0.075+0.007) and the coefficient of price history is positive 0.007 when buy dummy is zero (or for the case of sell imbalances). Together it implies that the price impact (buy – sell) asymmetry will turn negative as the price history increases. As expected, price impact of both buy and sell imbalances is higher for high information asymmetry stocks. The price impact of buy imbalances is a decreasing function of price history whereas price impact of analyst dispersion increases the buy permanent price impact after considering the interaction between price history and analyst dispersion. For sell imbalances the impact of analyst dispersion is positive and is of larger magnitude compared to that for buy imbalances and price asymmetry is an increasing function of price history. We also run the regression with NPPI for t+5 and t+10 days

with the same set of independent variables and find that the results become stronger and support our findings in Tables 4 and 5. 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 for stocks with higher analyst dispersion.

The coefficients on control variables are consistent with prior research. Contemporaneous market condition variable has a statistically significant positive coefficient for purchases and a statistically significant negative coefficient for sells. Taken together, the two coefficients imply that price impact asymmetry is positive in up markets and negative in down markets. Price impacts of both buys and sells are generally lower for large market capitalization stocks.

[Insert Table 5 about here]

3.6. Robustness Tests

In this section 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 control for liquidity considerations and obtain qualitatively similar results for price impact asymmetry.

3.6.1. A Stricter Criterion for Defining Price Run-Ups

A key variable in our analysis is the history of price run-ups. We search through the CRSP database to classify each calendar trading day into one of the three price history groups, which are 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 create a zero price run-up category by requiring 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 also represents the tick size in the earlier part 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 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 2.92 million stock days with price run-ups as compared to 3.57 million stock days of price run-ups without the adjustment of transaction costs. The reduction in asymmetry between 1 day run-up and 6 to 10 day run-up is negative and equals -69 bps, -112 bps, and 116 bps, respectively, for all the three price impact measurement windows of *t*+1, *t*+5, and *t*+10 from the trade date.

3.6.2. Bid-Ask Bounce and Price Impact Computation

Since we are mainly interested in understanding the asymmetry in the information content of institutional trades, it is important that we control for any asymmetry induced by pure liquidity considerations. Could bid-ask bounce contribute significantly to the difference in the price impact of buys and sells? Specifically, could spreads be higher for stocks with a higher level of idiosyncratic risk? Prior literature on institutional trading has not explicitly examined the role of bid-ask spreads. We address this concern in two different ways.

First, as a simple preliminary check, we obtain percentage effective bid-ask spreads for high and low idiosyncratic risk groups based on Hasbrouck (2009). We find that the spread for the high idiosyncratic risk group is about three times the spread for the low idiosyncratic risk group (0.15% versus 0.05%). Nonetheless the positive price impact asymmetry at the beginning of the run-up and its reduction to the point of turning negative after prolonged run-up still hold after subtracting the corresponding effective spread from the price impact of each group.

Second, we follow the more rigorous approach and use transaction data rather than closing prices to calculate price impact. Instead of closing prices, we use three alternative transaction prices, namely, mid-quote to mid-quote, bid-to-bid, and ask-to-ask. Again, our asymmetry and its reduction remain robust (not tabulated for brevity but available upon request). All results point to the conclusion that liquidity effects do not alter the asymmetry patterns in any major way. After controlling for bid-ask bounce, we continue to find evidence supporting the notion that the asymmetry in permanent price impact is driven mainly by how institutional constraints affect information content.

3.6.3. 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. The 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 remain the same. For example, PPI asymmetry for 1 day run-up is 52 bps when our sample is restricted to trades completed within single day compared to 53 bps for all orders in Panel A of Table 3 and the reversal for t+1 is -49 bps for robustness compared to -42 bps in Table 3.

3.6.4. Robustness tests regarding alternative explanations

To ensure that the results are driven by the asymmetric use of positive and negative information by institutions, we need to rule out alternative explanations for the empirical results we find. For example, several concerns are that the decrease in price impact of buy trades conditional on price run-ups could be due to portfolio rebalancing (Calvet, Cambell and Sodini, 2009) or disposition effect (Frazzini, 2006). We rule out these alternative hypotheses by carefully examining the

trading volume around price run-ups in our data. Both portfolio rebalancing and disposition effect would suggest a tendency of investors to sell their winners and to hold on to their losers. Thus, if these effects are the driving forces of institutional trades, we expect more sells than buys and also heightened sell volume after a price run-up.

Let us first consider portfolio rebalancing. If there is a price run-up in a stock, then due to the increased weight of the stock, institutions will rebalance their portfolio by selling some of the holdings in the stock. Hence we should see more "sell" trades in the stock. Similarly for disposition effect, one should expect to see a net selling in a stock that has witnessed a price run-up. Contrary to portfolio rebalancing and disposition, our sample shows that number of stock days that institutions sell is a lot lower than those of institution buys, conditioning on a price run-up; also the average sell volume is generally monotonically lower (not higher) compared to the buy volume after a price run- up. These results rule out the portfolio rebalancing and disposition as explanations for our findings of the price impact asymmetry; rather it the asymmetric use of positive and negative information due to institutional constraints which seem to drive the price impact asymmetry.

4. Conclusions

Using a comprehensive dataset from Ancerno, 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 theoretical model (Saar, 2001) concerning the asymmetric use of information by institutional traders under changing constraints at different stages of price run-ups. Our measure of the permanent price impact of institutional trading imbalance improves upon the assumption in prior literature that considers institutional

trades greater than 10,000 shares only. 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 reversal 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, and also informational characteristics of stocks. 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 related to capital, diversification, and short selling. 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 generate excess returns under certain conditions. Academic models may therefore benefit from including the entire set of determinants of price impact asymmetry.

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Table 1: This table is based on institutional trading data compiled by Ancerno. We report summary statistics for all trades in the data. Data period is from 2001 to 2012. Panel A provides average firm characteristics and Panel B describes the sample characteristics at the order and transaction levels. Panel C reports the distribution of stock days across different periods of price run-up. 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 trade.

Panel D has the summary of explanatory variables. Trading intensity is defined as the monthly trading volume in a stock divided by the number of shares outstanding at the beginning of the year. Idiosyncratic volatility is estimated for each calendar month, as mean squared errors from the regression of excess daily returns of each individual stock on the Fama-French three factors: *Rm-Rf*, *SMB*, and *HML*. Analyst forecast dispersion is defined as 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. Price dispersion is calculated as the percentage difference between the highest and the lowest trading prices in the 90 calendar days just prior to the arrival of institutional orders.

Panel A: Sample Characteristics

Number of Securities	4,799
Average Market Capitalization (billion $)	2.99
Volume Weighted Share Price ($)	30.45
Average Daily Volume (million)	3.80

Panel B: Institutional Trades and Buys and Sells

Total Number of Trades (million)	42.84
Total Number of Stock days (million)	7.29
Number of Stock Days Classified as Buys (million)	3.94
Number of Stock Days Classified as Sells (million)	3.33

Panel C: Comparison of NIT Control Sample and Ancerno

	Ancerno	NIT Control
Average Securities Traded Every Day	2,416	1,989
Average Market Capitalization (billion $)	2.99	2.22
Volume Weighted Share Price ($)	27.98	18.63
Average Daily Volume (million)	3.80	2.09

Panel D: 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

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 being1, 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 from CRSP for the period 1996-2012. Price impact is averaged across stock days and weighted using the institutional imbalance. Price impact asymmetry (*PIA*) is defined as the difference between the permanent price impact of Buy and that of sell. The sample is divided into three groups based on past price run-up of 1 day, 2-5 days, or 6-10 days. Price history is defined 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. Price impact asymmetry (*PIA*) for each price history group is defined as the difference between the permanent price impact of Buys and that of Sells**.** T-statistics are for paired two tails tests and are adjusted with the Newey-West procedure and presented in parentheses.

	PI t+1			***PI t+5***			***PI t+10***		
	Buy	**Sell**	**Asymmetry**	**Buy**	**Sell**	**Asymmetry**	**Buy**	**Sell**	**Asymmetry**
PPI	0.74	0.55	**0.19**	0.94	0.18	**0.76**	1.04	0.07	**0.97**
t-stat			*3.00*			*10.60*			*11.14*
MPPI	0.75	0.56	**0.19**	0.88	0.33	**0.55**	0.89	0.29	**0.60**
t-stat			*3.16*			*8.01*			*7.54*
BPPI	0.73	0.58	**0.15**	0.82	0.36	**0.46**	0.77	0.34	**0.43**
t-stat			*2.54*			*6.66*			*5.46*

Table 3. The Reduction of Price Impact Asymmetry

The Table shows the permanent price impact asymmetry divided into three groups on past price performance of 1 day, 2-5 days, or 6-10 days. We report results with three values of *n* (1, 5, and 10 days after a trade). Price history is defined as the number of days of consecutive positive market adjusted returns in the stock just prior to the arrival of institutional trade. Price impact is averaged across stock days within 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 no 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 that were traded minus the average price impact of stocks that were not traded. T-statistics are for paired two tail tests and are adjusted with the Newey-West procedure and presented in parentheses.

Price History	***PI t+1***			***PI t+5***			***PI t+10***		
	Buy	**Sell**	**Asymmetry**	**Buy**	**Sell**	**Asymmetry**	**Buy**	**Sell**	**Asymmetry**
Panel A: PPI									
1	0.89	0.37	**0.52**	0.95	0.14	**0.81**	1.14	0.24	**0.89**
+2 to +5	0.77	0.49	**0.28**	0.91	0.27	**0.64**	1.04	0.08	**0.96**
+6 to +10	0.55	0.46	0.09	0.64	0.41	**0.22**	0.70	0.71	-0.01
Magnitude of Reduction (+6 to +10 minus +1)			**-0.42**			**-0.59**			**-0.91**
t-stat			(2.14)			(2.08)			(2.25)
Panel B: MPI									
1	0.88	0.50	**0.38**	0.88	0.32	**0.56**	0.97	0.03	**0.94**
+2 to +5	0.78	0.60	**0.17**	0.82	0.40	**0.42**	0.87	0.32	**0.54**
+6 to +10	0.49	0.58	-0.09	0.45	0.63	**-0.18**	0.34	0.87	**-0.53**
Magnitude of Reduction (+6 to +10 minus +1)			**-0.46**			**-0.74**			**-1.46**
t-stat			(1.99)			(2.42)			(4.02)
Panel C: BPI									
1	0.86	0.53	**0.33**	0.83	0.37	**0.46**	0.84	0.13	**0.70**
+2 to +5	0.75	0.61	**0.15**	0.74	0.47	**0.27**	0.72	0.43	**0.29**
+6 to +10	0.46	0.60	-0.14	0.35	0.76	**-0.41**	0.27	0.96	**-0.69**
Magnitude of Reduction (+6 to +10 minus +1)			**-0.47**			**-0.87**			**-1.39**
t-stat			(3.07)			(3.87)			(3.22)
Panel D NPPI									
1	0.98	0.30	**0.68**	1.12	0.29	**0.82**	1.24	0.25	**0.99**
+2 to +5	0.83	0.39	**0.45**	1.18	0.47	**0.71**	1.08	0.28	**0.81**
+6 to +10	0.61	0.42	**0.19**	0.97	0.69	**0.28**	1.00	1.14	**-0.14**
Magnitude of Reduction (+6 to +10 minus +1)			**-0.49**			**-0.55**			**-1.14**
t-stat			(2.30)			(2.05)			(2.51)

Table 4. Price Impact Asymmetry: Past Price Run-up and Information Variables

Permanent Price Impact PPI_{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 A1, analyst forecast dispersion in Panel A2, trading intensity in Panel B, and price dispersion in Panel C. Idiosyncratic volatility is the residual estimated from the Fama-French three factor model. Analyst forecast dispersion or Analyst Dispersion is defined as the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts divided by the share price. Price Dispersion is calculated as the percentage difference between the highest and the lowest trading prices in the 90 calendar days just prior to the arrival of institutional orders. Trading Intensity is defined as the monthly trading volume in a stock divided by the number of shares outstanding at the beginning of the year. Within each panel, we form high and low information asymmetry groups using median values as cut-off points.). T-statistics are adjusted with the Newey-West procedure. Bold numbers indicate significance.

Price Run-up	***High Info***			***Low***			***High-Low***
	Buy	**Sell**	***Asymmetry***	**Buy**	**Sell**	***Asymmetry***	(t-stat)
Panel A1 Idiosyncratic Volatility							
1	1.17	0.31	**0.86**	0.56	0.37	**0.19**	**0.67**
							(3.54)
+2 to +5	1.11	0.33	**0.79**	0.46	0.48	-0.02	**0.80**
							(4.51)
+6 to +10	0.75	0.70	0.05	0.26	0.76	**-0.50**	**0.55**
							(2.92)
Difference (+6 to +10 minus +1)			**-0.82**			**-0.69**	
t-stat of difference			(2.72)			(4.06)	
Panel A2 Analyst Forecast Dispersion							
1	1.02	0.36	**0.66**	0.64	0.33	**0.31**	**0.35**
							(2.06)
+2 to +5	0.97	0.47	**0.51**	0.53	0.37	0.16	**0.35**
							(2.19)
+6 to +10	0.70	0.67	0.03	0.27	0.38	-0.11	0.14
							(1.35)
Difference (+6 to +10 minus +1)			**-0.63**			-0.42	
t-stat of difference			(2.23)			(1.44)	
Panel B Trading Intensity							
1	1.02	0.43	**0.58**	0.44	0.17	**0.28**	**0.30**
							(2.29)
+2 to +5	0.93	0.51	**0.41**	0.39	0.23	**0.16**	**0.25**
							(2.41)
+6 to +10	0.65	0.58	0.07	0.21	0.40	**-0.19**	**0.25**
							(2.06)
Difference (+6 to +10 minus +1)			**-0.52**			**-0.46**	
t-stat of difference			(2.47)			(3.10)	
Panel C Price Dispersion							
1	1.26	0.37	**0.89**	0.39	0.32	0.07	**0.82**
							(4.84)
+2 to +5	1.06	0.49	**0.56**	0.43	0.32	**0.11**	**0.45**
							(2.84)
+6 to +10	0.67	0.51	0.17	0.27	0.64	**-0.36**	**0.53**
							(2.32)
Difference (+6 to +10 minus +1)			**-0.73**			**-0.44**	
t-stat of difference			(1.98)			(2.32)	

Table 5: Price Impact Asymmetry regression results

The table shows the regression results where the dependent variable is the NIT (No Institutional Trade) adjusted Permanent Price Impact, ***NPPI***; t+n denotes the Permanent Price Impact after n days. History, the key explanatory variable, is defined as the number of consecutive days that the stock has positive returns over the market. Buy dummy equals one for buys and zero for sell trades. Analyst forecast dispersion or Analyst Dispersion is defined as 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. 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.

	$NPPI_{t+1}$	$NPPI_{t+5}$	$NPPI_{t+10}$
Intercept	0.263***	0. 416***	0.390***
Buy Dummy	0.522***	0.580***	0.552***
Price History	0.007**	0.008*	0.016*
Buy dummy x Price History	-0.075***	-0.148***	-0.188***
Buy dummy x Price History x Analyst Dispersion	0.0016*	0.0074*	0.0149***
Analyst Dispersion	0.048***	0.029***	0.027***
Buy Dummy x Analyst Dispersion	-0.042***	-0.030***	-0.039***
Firm Size	-0.077***	-0.068***	-0.055**
Market Condition	0.020***	0.066***	0.109***
Inverse of Stock Price	-0.101***	-0.230***	0.521***
Number of observations	2,965,342	2,965,342	2,965,342
Adjusted R Square	0.004	0.004	0.006

Figure 1: Price Impact Asymmetry and Price History

This graph plots the market adjusted permanent price impact of institutional buy imbalances, institutional sell imbalances, and the asymmetry between buy and sell imbalances on the vertical axis. For a given day, each stock, i, traded by institutional investors is assigned a direction (+1 or -1) based on whether the institutional trading imbalance ($\sum_i Volume_{buy}$- $\sum_i Volume_{sell}$) is positive or negative respectively. Price impact asymmetry is defined as the difference between market 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. Market adjustment is implemented by subtracting the market-wide returns in the corresponding period. Price history on the horizontal axis ranges from 1 day of price run-up to +10 days of consecutive price run-ups.