Trading Activity, Price Patterns and Overreaction*

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Abstract

This paper considers long run price reactions after periods of large positive and negative order flow imbalance. The relation between investors' actions, in the aggregate, and future returns is interesting because it can yield insight into how investors react to the information that led them to trade. The results indicate that returns are negatively related to firm-specific order flow imbalance. This result is consistent with the predictions of a general overreaction story. Moreover, if periods of large positive/(negative) firm-specific order flow imbalance are periods of positive/(negative) private information, the results are consistent with the static overconfidence model of Daniel, Hirshliefer and Subrahmanyam (1998), but not with their biased self-attribution model that is developed to explain momentum.

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1 Introduction

This paper examines the relation between trading activity and future returns at horizons significantly longer than those considered in the previous literature. Similar issues have been addressed in the market microstructure literature (i.e. the price impact of shocks to trading activity), however I am not aware of any work that deals with the relation between firm-specific trading activity and future returns at monthly frequencies. The relation between firm-specific order flow and future returns is interesting because order flow can be thought of as a noisy proxy for investor reactions to new information. Periods with large, positive/(negative) order flow are periods where investors in the aggregate sought to purchase/(sell). Apart from liquidity trade, this behavior indicates that as a group investors believed, rightly or wrongly, that buying/(selling) during this period was a profitable strategy. As I argue later, this means that examining price reactions after periods of heavy buyer or seller initiated trade provides evidence about whether investors react properly, overreact or underreact to information.

If we are willing to assume that order flow only reflects informed trade and a noise component due to liquidity trade, the relation between order flow and future returns can be used to examine the hypotheses in Daniel, Hirshleifer and Subrahmanyam (1998) (DHS). DHS present two models with overconfident investors, the "static overconfidence" model and the "biased self-attribution" model. Both models are based on the hypothesis that investors overreact to *private* signals. While DHS abstract from microstructure issues, I appeal to the large literature in market microstructure that argues that private information gets incorporated into prices through the trading activities of informed traders. If trades only reflect the actions of informed traders and a noise component due to liquidity trade, then order flow can be thought of as a noisy proxy for a *private* information shocks[1]. Abnormal price changes subsequent to extreme order flow events can then be used to examine the DHS hypothesis. Specifically, if informed investors overreact to their private information in one of the ways suggested by DHS, then we expect subsequent abnormal price movements similar to those predicted by their models[2]. On the other hand, if informed investors are rational and if the trade data are publicly available and are of low cost to analyze, then we expect that there would be no subsequent abnormal price movement.

The results indicate that firm-specific order flow is negatively associated with subsequent price movements. A zero-investment portfolio formed by taking a long position in the firms with the highest firm-specific order flow over the past three to twelve months and an offsetting short position in firms with the lowest firm-specific order flow in the same period has economically and statistically significant negative average abnormal returns over subsequent months. Depending on the holding period, the average abnormal returns[3] to the hedge portfolio range from around -90 basis points per month to around -40 basis points per month. It is also interesting to note that these negative average returns obtain despite the fact that the high order flow portfolios have much higher ranking period returns than the low order flow portfolios. This is a surprising result in light of the momentum literature

[1] This assumption effectively defines public information as information that does not lead agents to trade. Issues related to this definition are discussed further below.

[2] I discuss the two models in more detail below.

[3] In this context, by "returns" I mean the profits per dollar long. Strictly speaking, the long/short portfolio has an infinite return since it is a zero-investment portfolio.

which documents that the stocks with high recent returns tend to outperform stocks with low recent returns.

Without making any assumption about the kind of information that motivates investors to trade, these results can be thought of as consistent with a simple overreaction story. Under the stronger assumption that order flow is a noisy proxy for informed trade, the results are consistent with the DHS's static overconfidence model, but not their biased self-attribution model.

This essay is organized as follows. Section 2 briefly reviews the relevant literature. Section 3 discusses the data. Section 4 contains the results and interpretation. Section 5 concludes.

2 Literature Review

Recently, a number of papers have considered the relation between total trading volume and future returns. For instance, Gervais, Kaniel and Mingelgrin (2001) document that firms with high/(low) trading volume over a day or a week tend to increase/(decrease) in price. Lee and Swaminathan (2000) find that momentum is stronger in stocks with high trading volume. Unlike these studies, this paper considers the relation between *net* trade, or order flow, and future returns. Chordia et. al. (2002) study a related, but distinct issue. They investigate the relation between market order flow and market returns at daily frequencies. While they focus on systematic liquidity effects, the current study deals with firm-specific order flow and abnormal returns to shed light on some popular behavioral explanations for capital market anomalies.

One motivation for this research is to provide evidence on how investors react to information, without making an explicit assumption about whether the information is public or private. There are a large number of papers arguing that investors either under or overreact to information, without specifying whether the information is public or private. De Bondt and Thaler (1985), Lakonishok, Shleifer and Vishny (1994), LaPorta, Lakonishok, Shleifer and Vishny (1997), among many others, have suggested that investors overreact to information[4]. Under the overreaction hypothesis, we would expect that firms experiencing unusual buyer/(seller) initiated trading activity would experience subsequent price decreases/(increases). On the other hand, some researchers, including Jegadeesh and Titman (1993) and Bernard and Thomas (1990), hypothesize that investors underreact to information. They argue that this underreaction creates the price and earnings momentum phenomena. If underreaction is a dominant characteristic of investor behavior, then it is reasonable to expect that firms experiencing unusual buyer/(seller) initiated trading activity would experience subsequent price increases/(decreases). As noted above, the results in this paper support the overreaction hypothesis.

Another key motivation behind this paper is to examine the DHS model. Some, such as Fama (1998), have noted that if a behavioral theory is to replace the efficient markets hypothesis then it will have to explain why investors overreact at some times and underreact at others. DHS present such a model[5]. They imagine a world with both informed and uninformed agents. In this world, the informed agents overreact to their private signals.

[4]See Fama (1998) for a detailed summary of this literature.

[5]Barberis, Shleifer and Vishny (1998) present another. However, their model does not involve the distinction between public and private information.

The intuition behind this notion is that in order to get private trading signals, agents must expend effort and resources. During this process, the agents become "attached" to their personal signals. As a result, they are overconfident about their signals in the sense that they overestimate their signal precision. On the other hand, all agents properly interpret the precision of information seen and understood by the public at large.

DHS present two parameterizations for the informed agent's overconfidence: static overconfidence and biased self-attribution. An agent subject to static overconfidence overestimates his private signal precision by the same amount regardless of the circumstances. By contrast, an agent exhibits biased-self attribution if the agent is overconfident about her private information and becomes more so in the face of public information confirming her private signal. Under static overconfidence, the agent's initial overreaction is corrected as public information is revealed. This produces a pattern of reversals after private information arrival. In the case of biased self-attribution, the increase in overconfidence causes a period of return *continuation* after the initial overreaction. This period of return continuation is what allows the biased self-attribution model to generate the price and earnings momentum effects of Jegadeesh and Titman (1993) and Bernard and Thomas (1990). Since the static overconfidence model only generates reversals, it is not consistent with momentum phenomena. However, as with the static model, under biased self-attribution the continuation period eventually ends as public information arrives and the initial overreaction is corrected.

In order to consider the DHS hypotheses, the current study turns to the large market microstructure literature that deals specifically with private information and its impact on prices. Surprisingly, there has been very little exploration of the link between the behavioral literature that deals with how investors react to information and the microstructure literature that deals with how information gets into prices. Like the DHS model, the market microstructure literature analyzes situations involving asymmetrically informed agents. In microstructure theories, informed agents' trades convey information to market makers and therefore impact prices. However, due to the presence of liquidity trade, private information is not observable to either market makers or econometricians. This complicates empirical assessments of private information's impact on prices.

Despite the problems, a number of studies have attempted to operationalize the notion of private information. Hasbrouck (1991, 1993) use trade and quote revision data to compute the permanent impact of a trade innovation on an individual stock's price. Hasbrouck then uses the price impact of a typical trade shock as a summary measure of the informativeness of the trade in the stock. In a related vein, a series of papers including Easley, Kiefer, O'Hara (1996, 1997a, 1997b), Easley, Kiefer, O'Hara and Paperman (1996, 1998), Vega (2001) and Easley, Hividkjaer and O'Hara (2002) develop and/or employ a measure of the probability of informed trade, called the PIN measure. Like Hasbrouck (1991, 1993) these papers rely on the idea that trade reflects only liquidity trade and private information. Unlike Hasbrouck (1991,1993) these papers employ a model that puts the econometrician in the place of a hypothetical market maker attempting to infer the arrival of informed trade from trading activity. For any particular stock, the econometric routine essentially identifies a "normal" level of trade. This level of trade is associated with liquidity trade. The PIN measure is computed by identifying periods with abnormally high (relative to the normal level of liquidity trade) numbers of buy or sell orders as periods where private information has arrived.

The interpretation of firm-specific order flow as a proxy for private information shocks reflects similar intuition. If we assume, as the papers involving the PIN measure do, that order flow reflects only informed trade and a noise component due to liquidity trade, then it is likely that periods of abnormally high buyer/(seller) initiated trading activity are periods in which informed agents sought to trade on their private signals. In effect, the interpretation of firm-specific order flow as a proxy for informed trade identifies the abnormal levels of order flow by conditioning on the market. Under this assumption, we can use the relation between firm-specific order flow and future returns to examine the hypothesis behind the DHS models rather than just simple over and underreaction stories.

It is worth noting that the DHS models abstracts from trading activity. Thus, it may seem odd to use trade based empirical methods to examine the hypotheses behind the models. I argue that this is a reasonable approach for two reasons. First, examining the DHS hypothesis requires some proxy for the arrival of private information. Despite the fact that the models abstract from trading activity, order flow is a natural and sensible instrument for the actions of informed individuals. Second, it seems likely that the DHS models could be modified to include trading activity. For instance, a liquidity trader could be added to the models. The uninformed agents could then be thought of as a market maker trading with both the informed and liquidity traders. The informed agents would presumably make larger trades than a rational agent would. If, as in the original DHS models, the uninformed (rational) agent is not willing to take large positions against the informed agents because of, say, risk aversion, then the implications of the DHS models would obtain.

Chan (2001) also examines the DHS models by considering price reactions after the arrival of private information. Unlike this paper, Chan (2001) uses news releases and event study framework. Chan sorts stocks with large returns in a one month ranking period into two categories: those with identifiable news items (defined as a news item on the Dow Jones News Wire) released during the ranking period and those without news items in the ranking period. One interpretation of the news/no news distinction is that if a stock experiences a big return and no news during a period, then this was a period in which private information moved the price. On the other hand, if a stock has a large return and a news item, then this was a period where public information moved the price. Chan finds that stocks with news items and large returns in the ranking period subsequently experience price momentum, while those with no public news and large returns tend to experience reversals. Chan interprets these results as consistent with the DHS hypothesis of underreaction to public information (i.e. momentum following news events) and overreaction to private information (i.e. reversals following no-news events).

There are a number of caveats to this approach. One problem is that his no-news category may simply be a group of stocks with public news releases that were not reported on Dow Jones. For instance, analyst revisions are not included in his sample nor are press reports not covered by Dow Jones. Perhaps more importantly, it seems likely that news items about one firm may dramatically impact other firms (for instance, competitors), without the other firms being specifically mentioned in the news items. This also might be considered public information, but would not show up in a Dow Jones news search. Thus, the "news" versus "no-news" categories may actually reflect the distinction between "Dow Jones news" and "other public news" rather than the distinction between public and private information.

Another problem relates to the definition of private information. If scarce resources must be consumed to transform a public news release into a private trading signal, then the "news" / "no news" categorization does not represent as clear a distinction between private and public information events as it might seem. I argue that in many cases public news releases and publicly available information only amount to the raw material for a signal of an asset's value.

For instance, translating the qualitative information in a news article into the fundamental value for a stock can be a costly and difficult process. Likewise, extracting estimates of fundamental values from complicated sets of publicly available financial statements requires substantial skill and effort. I argue that only agents who apply the resources and skill to perform these analyses actually receive a value signal. In this case, the signal has to be considered private since only agents who expend resources to extract it actually get the signal. Furthermore, the agents would not be willing to expend resources to extract the signal from the public information if the signal itself became public information[6]. This logic makes it less clear that periods with public news releases are periods of public signals. The

[6]This argument is related to the those made in more detail in Grossman and Stiglitz (1980). In their model, signals have to be purchased like any other good. Agents are willing to purchase signals only if they believe they will receive commensurate expected private benefits.

series of papers (listed above) that develop and use the PIN measure also take the position that private information should include private interpretations of otherwise public news. As Easley, O' Hara and Paperman (1998) state:

> "In effect, we define information events as public if they do not affect trading. Such events may cause price changes, but little or no trade should be generated by a truly public information event. To the extent that seemingly public information events affect trade, they have a private component (such as understanding how to use this particular information) and we classify them as private information events."

By using a definition of private information based on trading behavior, I side-step the problems in identifying private information associated with the event based approach. Of course, the trade based approach requires that firm-specific order flow be a good proxy for the arrival of private information.

Finally, a few studies have used trade flows of various kinds to study the impact of private information on prices. Albuquerque, Bauer and Schneider (2002) regress monthly international equity flows on past monthly flows and other predictive variables. They then use the residuals from this regression as a measure of the private information in these flows. They find evidence of a common factor in their private information measures across countries and use it to help explain the cross-section of international equity returns. Lastly, Vega (2001) considers the relation between the PIN measure mentioned above and the earnings announcement drift phenomenon documented by Bernard and Thomas (1990) among others.

She finds that firms with a higher probability of informed trade have larger abnormal returns after earnings announcements.

3 Data

To minimize the noise liquidity trade adds to the analysis, I seek to remove as much of the variation in order flow related to liquidity trade as possible. To do so, it is useful to think of order flow as composed of two orthogonal components, market related order flow and firm-specific order flow. Each component reflects liquidity trade and informed trade. However, intuition and empirical evidence suggests that market related order flow is likely to contain a larger liquidity trade component than firm-specific order flow. It is easy to imagine agents producing private information about individual firms by analyzing financial statements, products and prospects for growth. This is ostensibly what analysts do and what many active mutual fund managers base their trades on. Much of this component would be 'diversified away' when order flow from a large number of firms is combined into market order flow. On the other hand, variation due to systematic liquidity trade would not be diversified away when aggregating to market order flow. Systematic liquidity trade might happen when shocks to the consumption or the investment opportunity set cause investors to rebalance their equity portfolios, or when investors reallocate wealth from stocks to bonds during a so-called 'flight to quality'.

This intuition is consistent with the evidence in Chordia et. al. (2000). Chordia et. al (2000) run multiple regressions of bid/ask spreads on market and firm volume measures and find that spreads are decreasing in market volume, but increasing in firm volume. This suggests that firm-specific trading activity tends to be information related while market related activity is more liquidity related. Based on this reasoning and evidence, I analyze the relation between firm-specific order flow and future returns. Firm-specific order flow is computed as the residual from a regression of individual firm order flow on the aggregate order flow for the market as a whole.

To gather the trade data necessary to compute firm-specific order flow I turn to the NYSE Trade and Quote (TAQ) database. I consider only stocks that trade on the NYSE. Each trade and quote in the database is time stamped. I exclude trades and quotes posted before 9:35 A.M. and after 4 P.M. This is to exclude opening batch trades and trades that happen after the close. I exclude all trades with special settlement requirements. I further exclude all trades of zero size and all quotes where either the bid or the ask price was zero. I also exclude all trades where the price was more than 50% higher than both the preceding and following trade. Similarly, I exclude all quotes where the bid or the ask was more than 50% higher than both the preceding and following quote. For those stocks whose price exceeds $1, I exclude all quotes where the proportionate spread was greater than 100%. I take these steps to filter out data errors.

Since the trades in the TAQ database are not identified as buyer or seller initiated, I employ the Lee and Ready (1991) algorithm to classify each trade as a buy or a sell. Briefly, the algorithm classifies trades as buys or sells with reference to the prevailing quote. The prevailing quote is the current quote, or the quote in effect 5 seconds ago if the current quote is less than 5 seconds old. If a trade price is closer to the ask than the bid, the trade is classified as a buy. Buys are signed as positive, sells negative. For those trades that occur at the mid-point of the prevailing bid/ask spread, I use a tick-test to infer the trade direction, as follows. Trades at the mid-point are classified into four categories: upticks, downticks, zero-upticks and zero-downticks. Upticks/(downticks) are trades that occur at a price higher/(lower) than the previous trade. Zero-upticks/(downticks) are trades where the price was the same as the previous trade, but where the previous trade was an uptick/(downtick). All upticks and zero-upticks are classified as buys, other trades are classified as sells.

The use of the Lee and Ready algorithm, while unavoidable, introduces errors in the classification of trades. A number of studies have considered the error rate associated with this algorithm, including Odders-White (2000), Lee and Radhakrishna (2000) and Ellis et. al (2000). These studies find that it is between 85 and 93 percent accurate, depending on the sample of stocks studied. The presence of measurement error reduces the statistical power of my tests. This is a small matter, however, since my results do not appear to lack precision. Of greater potential concern is a systematic bias in the algorithm. Odders-White (2000) presents evidence that certain transactions, for instance those inside the bid-ask spread and small transactions, have substantially higher mis-classification rates. If these transactions are heavily weighted toward true buys or true sells then the error rate adds a systematic positive or negative bias in raw order flow. However, when I regress observed order flow on market order flow the bias in the measurement error gets absorbed into the intercept. Therefore, firm-specific order flow reflects measurement error, but not any bias imparted by the algorithm.

For each firm-month, I compute the order flow as the net number of shares traded during the month. This leaves me with a time series of order flow and closing quotes for each stock on the NYSE from January 1993 to November 2001. Since most stocks had changes in their number of shares outstanding during this period, I adjust the quotes using the cumulative adjustment factor for shares outstanding provided by CRSP. The adjusted quotes are thus stated based on a common number of shares outstanding. I compute a daily time series of percentage quote revisions, $r_{i,t}$, using the adjusted closing quotes. If $q_{i,t}$ is the mid-point of the adjusted closing quotes today, then $r_{i,t} = \frac{q_{i,t}+d_{i,t}-q_{i,t-1}}{q_{i,t-1}}$, where $d_{i,t}$ is the amount of the quarterly dividend, if any, on ex-dividend days. Dividends are included to account for the fact that quotes drop by approximately the amount of the dividend per share on ex-dividend dates. I compute monthly quote revisions by compounding the daily r_t's. To account for the fact that the number of shares outstanding differs between firms, I normalize the order flow by dividing by the shares outstanding at the end of the previous month. Stock returns used in the portfolio results were collected from CRSP. Descriptive statistics for each of the variables can be found in Table I.

4 Results

To analyze the relation between order flow and returns at relatively long horizons, I employ a calendar time event study approach. This method has been widely used in the anomalies literature to uncover return patterns over intermediate and long horizons. A version of this approach was first employed by Jaffe (1973) and Mandelker (1974). Jegadeesh and Titman (1993) use a similar approach to document the well-known price momentum effect. Since

Jegadeesh and Titman (1993), versions of this design have been used in a large number of studies, including Chan, Jegadeesh and Lakonishok (1996), Chordia and Shivakumar (2002) and Chan (2001).

I also employ a method similar to the one used in Jegadeesh and Titman (1993). The only difference is that I sort firms into high and low categories based on their firm-specific order flow over the past k months rather than sorting firms into "winner" and "loser" categories based on their returns over the past k months as in Jegadeesh and Titman (1993). I consider ranking periods of one, three, six, nine and twelve months. I then examine the returns to a Jegadeesh and Titman (1993) portfolio long/(short) in the highest/(lowest) quintile of firm-specific order flow. I compute returns to portfolios with a variety of holding periods, from 1 to 24 months.

I choose these holding and ranking periods because most of the overreaction and under-reaction stories in the literature, including the equilibrium behavioral models, are intended to explain empirical regularities such as the book-to-market effect, the momentum effects or any of the various anomalies surrounding corporate events. These anomalies are evident at frequencies covering several months. Accordingly, this paper examines similar horizons. To assess the impact of market capitalization on the results, I divide the sample into two size groups: firms bigger than the median market capitalization and firms less than the median market capitalization.

The results can be found in Tables II, III and IV. Table II presents statistics for the ranking periods. For each ranking period, the average firm-specific order flow in the high order flow quintiles is positive and ranges from 1 percent of shares outstanding in the 1 month ranking period to between 7 and 10 percent of shares outstanding in the 12 month ranking period. The firm-specific order flow averages in the low quintiles all are negative and have similar magnitude to the high order flow quintiles. As expected, there is a substantial difference in the average ranking period returns between the high and low order flow categories. The high order flow groups have large, positive average ranking period returns. The low order flow quintiles typically have negative average returns.

Tables III and IV show that for both big and small stocks, in ranking periods longer than one month, the average holding period returns to the long/short portfolio are negative and significant in both an economic and statistical sense. The mean returns are typically around -50 basis points per month. The general pattern in most cases is for the average returns to be larger in the short holding periods and decline somewhat in longer holding periods.

It is interesting to note that the results for the one month ranking period differ from the longer ranking period results. For the one month ranking period the average returns to the long/short portfolio are positive, but small; less than 6 basis points per month and typically statistically insignificant. This is true of both the big and small firm groups.

It is also important to note that the differences in average returns to the high and low order flow portfolios do not appear to be due to differences in risk as measured by the CAPM or the Fama-French (FF) three factor model. Moreover, the differences do not appear to be a result of the momentum effect. Table V presents the alphas from time series regressions of the profits to the zero-investment portfolios on the excess market return, the FF model and the Carhart (1997) model. In almost every case, the sign, economic size and statistical significance of the alphas is similar to the average raw return. The exception is the twelve month ranking/one month holding period. The alpha for this portfolio is positive and very small in economic terms.

These results suggest a number of interesting points. First, whatever interpretation we give firm-specific order flow, it is related to future returns over much longer horizons than previously documented. Second, the relation between future returns and firm-specific order flow is the opposite of the relation between future returns and past returns documented in the momentum literature. We would expect, based purely on the momentum results, that the high order flow portfolio would have larger average returns than the low order flow portfolio because the high order flow portfolio has significantly larger ranking period returns than the low order flow portfolio. In contrast, we find that the high order flow portfolio has significantly lower average returns. It is possible, despite the fact that the high order flow portfolio has significantly larger ranking period returns than the low order flow portfolio, that the high order flow portfolio has a significantly lower momentum factor loading than the low order flow portfolio. In this case, the negative average returns documented in tables III and IV might be considered an artifact of the momentum effect. The Carhart (1997) alphas in table V indicate that this is not the case. The alphas are similar in sign and magnitude after controlling for the momentum factor.

This is an intriguing result because it suggests that firm-specific order flow is not driving the extreme ranking period returns experienced by firms in the momentum portfolios. If firm-specific order flow were driving the winners' and losers' extreme ranking period returns, we would expect that firms with high order flow would be winners and firms with low order flow would be losers. This is apparently not the case since the average returns and alphas to the long/short portfolio are the opposite of what we would expect given the momentum results.

This raises the question of how stocks in a winner/loser momentum portfolio get such extreme returns in the momentum ranking period in the absence of high/low order flow during the same period. The answer may be that public information events in the ranking periods are rapidly, but incompletely, incorporated into the market-makers' posted quotes. Under this scenario, the firms in the extreme portfolios experience events during the ranking period that are visible to market-makers so that quote adjustments can be made. However, the quote adjustment, while extreme, would have to be insufficient to explain the subsequent returns to the momentum portfolios. This would be consistent with Chan (2001)'s finding that firms that had big returns and Dow Jones news items in the ranking period subsequently experienced momentum.

Third, the results appear to be consistent with general overreaction stories rather than underreaction stories. Whether investors base their decisions on public or private information, in a pure underreaction story, we would expect to see return continuation after extreme buying and selling decisions. With overreaction, we expect to see reversals after extreme buying and selling behavior. Since average returns are lower after extreme buying behavior and higher after extreme selling behavior, the results are consistent with the general overreaction stories.

Fourth, as discussed above, if we are willing to assume that firm-specific net order flow proxies for informed trade, the results for the 3 to 12 month ranking periods are consistent, for the most part, with the static overconfidence hypothesis, but not with the biased self-attribution hypothesis. Recall that under the static overconfidence hypothesis, we expect reversals after the arrival of private information. Under the biased self-attribution hypothesis we expect to see a period of continuation before the reversals begin. Ranking periods of three months and above show large negative returns (and alphas) to the long/short portfolio for all holding periods. At the same time, during the ranking period the high order flow portfolio has a higher return than the low order flow portfolio. This is as expected under the static overconfidence model, namely a reversal of price movements associated with informed trade. If the biased self-attribution model were true, one would expect that there would be positive average returns in at least some of the shorter holding periods. This would be indicative of continuation. In fact, only the twelve month ranking period/one month holding period has a positive average abnormal return.

Some might argue that the assumption that order flow consists only of informed trade and liquidity trade is too strong and that order flow could reflect trade based on publicly available information. This might call into question the interpretation of these results as consistent with the DHS static overconfidence hypothesis. This problem is not unique to this study; the question of whether trade reflects public information bedevils all studies that attempt to use trade data to identify private information including those using the PIN measure and the measures developed by Hasbrouck (1991,1993).

I concede that there may indeed be trade based on public information included in the firm-specific net trade. However, as I argued above, simply because a trade appears to be based on publicly available information does not mean it is not an informed trade. In many cases, publicly available information is of little use without the application of costly resources to turn the information into a trading signal. In this sense, the potential for non-liquidity trade based purely on public information with no private component seems much less likely.

On the other hand, one could argue that technical trading strategies or feedback trades cannot be considered informed trade. The argument here is that trade based purely on past price movements cannot be considered informed since it is based on price information that is virtually free to obtain. With this logic in mind, some might question whether price movements in the holding period are related to informed trade in the ranking period or to positive feedback trade in the ranking period. If the latter is true, the interpretation of the results as consistent with the DHS hypothesis could be called into question.

To deal with this problem, I adjust the firm-specific order flow as follows. First, for each firm, I compute the following VAR(10) using the daily sequence of quote revisions ($r_{i,t}$) and total order flow, $x_{i,t}$. This specification is similar to that used in Hasbrouck (1991, 1993) except that it is estimated on quote and order flow data that are aggregated to the daily level.

$$r_{i,t} = \beta_i x_{i,t} + \phi_{i,1,1} r_{i,t-1} + \cdots \phi_{i,1,10} r_{i,t-10} + \theta_{i,1,1} x_{i,t-1} + \cdots \theta_{i,1,10} x_{i,t-10} + u_{i,t}$$

$$x_{i,t} = \phi_{i,2,1} r_{i,t-1} + \cdots \phi_{i,2,10} r_{i,t-10} + \theta_{i,2,1} x_{i,t-1} + \cdots \theta_{i,2,10} x_{i,t-10} + e_{i,t}$$

Here $e_{i,t}$ is a measure of order flow purged of variation that is predictable based on quote revisions and order flow over the past 10 days. I then cumulate $e_{i,t}$ to the monthly level, firm by firm. This should act to mitigate the problem of including trade based on past price movements. As above, I then regress the monthly order flow on the market order flow to remove variation due to liquidity trade. I refer to the residual from this regression as adjusted firm-specific order flow.

For each of the ranking/holding period combinations, I form another Jegadeesh and Titman (1993) zero investment portfolio, this time using the adjusted firm-specific order flow as the ranking variable. The average returns to these portfolios can be found in Table VI. To conserve space, I report only the average returns to the zero investment portfolios. For ranking periods of three months or longer, the average returns are negative and economically and statistically significant. Moreover, the magnitude of the average returns is very similar to the average returns to the zero investment portfolios formed using firm-specific order flow.

Table VII presents the zero investment portfolio alphas with respect to both the CAPM, FF three factor model and the Carhart (1997) model. As was the case with the average returns, the alphas for the zero investment portfolios formed on adjusted firm-specific order flow are similar in all respects to the alphas from the zero investment portfolios formed on unadjusted firm-specific order flow. The large-firm alphas from the adjusted firm-specific order flow portfolios are typically slightly smaller in magnitude than the alphas from the unadjusted firm-specific order flow. The opposite is typically true for the small firms. The similarity of the average returns and alphas between the two sets of portfolios indicates that the presence of predictable or feedback trade within the month is not affecting the results.

Finally, I note that by being consistent with static overconfidence and inconsistent with biased self-attribution, these results present a challenge to the DHS hypothesis. Of the two hypotheses, biased self-attribution is the only one that can potentially explain the earnings and price momentum anomalies that have so puzzled researchers in recent years. Thus, while these results support a key DHS hypothesis, they do not support the DHS model that was developed to explain one of the most important capital market regularities uncovered in the past 30 years.

5 Conclusion and Suggestions for Further Research

Firm-specific net order flow is negatively related to future returns, over medium to long horizons. Zero-investment portfolios long/(short) in firms with high/(low) firm-specific order flow over the past three months to one year have negative average returns over the next one to twelve months. The average returns to these zero investment portfolios do not appear to be related to risk as measured by the CAPM or the FF three-factor model. Furthermore, the abnormal returns from the Carhart (1997) model suggest that this result is not driven by the momentum effect. Indeed, given the positive contemporaneous correlation between firm-specific order flow and returns, this result is exactly the opposite of what the momentum evidence would suggest.

One way to interpret these results is in terms of simple under and overreaction stories. In a simple overreaction/(underreaction) story we would expect to see negative/(positive) returns to a zero investment portfolio long/(short) in past high/(low) firm-specific order flow. These results are therefore consistent with overreaction rather than underreaction. If we are willing to assume that order flow consists only of informed trade and a noise component due to liquidity trade, a stronger interpretation is possible. Under this assumption, order flow proxies for private information events. Therefore, the results can be used to examine the DHS hypotheses related to overreaction to private information; namely static overconfidence and biased self-attribution. Since these results are indicative of long term reversals without any continuation period, they are consistent with the DHS static overconfidence model, but are not consistent with their biased self-attribution model.

There are a number of areas to explore in future work. First, the static overconfidence model suggests that returns attributable to private information events should be reversed on subsequent public information release dates. To investigate this, it would be interesting to examine the average returns to firms with high/(low) firm-specific order flow on, say, the three days surrounding each of the earnings announcements in the year following the ranking period. This would shed light on whether the overreaction is corrected around public information releases as DHS suggest.

Second, the evidence in the Barclay and Warner (1993) could be used to build an alternative proxy for informed trade. Barclay and Warner (1993) show that most of the cumulative price change on NYSE stocks is due to medium size trades. This is consistent with informed traders breaking up their trades to conceal their presence. Thus, including only medium size trades might yield an order flow measure that is more demonstrably related to informed trade. Demonstrating that the results are consistent using these proxies would increase the force of my argument and demonstrate robustness of the results.

Third, to further investigate whether firm-specific order flow is capturing informed trade, I could examine the average percentage spreads in the ranking period. If the bid-ask spreads were wider in the high and low firm-specific order flow category than in the middle category, there is evidence that the firms in the high and low firm-specific order flow categories experienced information events. Moreover, if spreads for firms in the extreme categories were wider during the ranking period than before or after, there is evidence that the ranking period was a period with significant informed trade.

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Table I: Descriptive Statistics

Presented below are descriptive statistics for various variables. OF is total firm order flow. Market OF is computed each month by summing the total net trading volume for each stock in the sample. RET is the monthly return to the stock and REV is the percentage quote revision, including dividends. Panel A presents the averages, medians and quartiles for each of the variables. These are the averages across the entire panel January 1993 to November 2001. Panel B presents the mean and median correlations between the various variables. Panel C presents the quartiles of the correlations. The correlations are computed firm by firm and the means, medians and quartiles are taken across firms.

Panel A:

Cross-Sectional Statistics:

	OF	**MOF**	**RET**	**REV**
Mean	0.002	-0.003	0.011	0.009
3rd Qrt.	-0.001	-0.002	0.019	0.015
Median	-0.002	-0.003	0.011	0.008
1st Qrt.	-0.005	-0.004	0.004	0.002

Panel B:

Correlations:

Means/Medians:

	OF	**MOF**	**RET**	**REV**
FSOF	1.000	0.278	0.277	0.208
MOF	0.352	1.000	0.102	0.104
RET	0.352	0.181	1.000	0.965
REV	0.320	0.201	0.896	1.000

Panel C:

1st/3rd Quartiles:

	OF	**MOF**	**RET**	**REV**
FSOF	1.000	0.416	0.413	0.368
MOF	0.155	1.000	0.181	0.191
RET	0.153	0.046	1.000	0.991
REV	0.100	0.048	0.848	1.000

Table II: Ranking Period Statistics

NYSE firms are split into two groups, those above and those below the median market capitalization. Within each group, each month firms are ranked into quintiles based on their firm specific order flow over the past one, thee, six, nine or twelve months. Firm specific order flow is defined as the residual from a regression of firm order flow on market order flow. Both firm and market net order flow are expressed as a percentage of total shares outstanding at the beginning of the period. The average returns and firm specific order flow during the various ranking periods for the big and small firms are presented below. High and low refer to the highest and lowest quintile of firm specific order flow during the ranking period in question. All numbers are in percent.

Ranking Period

	One Month		Three Months		Six Months		Nine Months		Twelve Months	
Big Firms										
	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow
High	4.48	1.17	10.06	2.92	16.60	4.59	22.64	5.91	28.52	7.13
Low	-2.27	-1.26	-1.48	-3.14	1.69	-4.81	5.21	-6.08	9.35	-7.14
Small Firms										
	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow	Avg. Return	Firm Spc. Ord. Flow
High	4.75	1.82	7.27	4.52	9.35	7.07	11.60	8.99	13.45	10.42
Low	-2.51	-1.93	-4.42	-4.74	-6.15	-6.87	-7.42	-8.27	-7.96	-9.32

Table III: Results for Small Firm H-L Portfolios Formed Using Firm-Specific Order Flow

Presented below are returns to a version of the Jegadeesh and Titman (1993) portfolio strategy, where instead of ranking on returns, large stocks are ranked on firm-specific order flow during the last one, three, six, nine or twelve months. Firm-specific order flow is the residual from a regression of total firm order-flow on market order flow. The group labeled High/(Low) are stocks in the highest/(lowest) quintile of order flow. The panel labeled H-L is the difference between the high and the low returns. This corresponds to the profits per dollar long to a zero-investment portfolio formed by taking a long position in the High group of stocks financed by an offsetting short position in the Low group of stocks.

		Ranking Period														
		One Month			**Three Months**			**Six Months**			**Nine Months**			**Twelve Months**		
Holding Period		**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**
	1	0.94	0.41	2.30	0.43	0.47	0.91	0.34	0.48	0.71	0.40	0.50	0.80	0.38	0.52	0.73
	3	0.91	0.41	2.22	0.47	0.48	0.97	0.41	0.50	0.82	0.47	0.51	0.91	0.42	0.54	0.78
	6	0.95	0.41	2.30	0.49	0.50	0.99	0.47	0.51	0.92	0.45	0.53	0.85	0.49	0.55	0.89
	9	0.94	0.42	2.22	0.55	0.51	1.08	0.46	0.53	0.88	0.51	0.55	0.94	0.47	0.57	0.83
High	**12**	0.93	0.43	2.15	0.50	0.53	0.94	0.52	0.54	0.96	0.48	0.56	0.85	0.54	0.58	0.92
	15	0.98	0.44	2.23	0.57	0.54	1.04	0.49	0.56	0.87	0.56	0.58	0.97	0.52	0.60	0.86
	18	1.02	0.45	2.27	0.54	0.56	0.97	0.59	0.57	1.02	0.56	0.60	0.94	0.46	0.62	0.74
	21	1.01	0.47	2.18	0.65	0.58	1.13	0.60	0.60	1.01	0.50	0.62	0.81	0.40	0.64	0.63
	24	1.11	0.48	2.34	0.68	0.60	1.14	0.54	0.62	0.87	0.44	0.64	0.69	0.47	0.66	0.72
	1	0.92	0.42	2.20	1.28	0.51	2.51	1.35	0.53	2.57	1.29	0.53	2.42	1.24	0.54	2.30
	3	0.89	0.41	2.15	1.10	0.50	2.18	1.10	0.52	2.11	1.09	0.53	2.07	1.09	0.53	2.04
	6	0.90	0.42	2.15	1.00	0.51	1.97	1.01	0.53	1.90	0.94	0.53	1.76	1.08	0.54	2.00
	9	0.88	0.43	2.06	0.95	0.52	1.84	0.90	0.53	1.69	0.99	0.54	1.83	1.05	0.55	1.92
Low	**12**	0.89	0.44	2.03	0.86	0.52	1.65	0.96	0.54	1.79	0.97	0.55	1.77	1.16	0.56	2.09
	15	0.94	0.44	2.11	0.97	0.53	1.81	0.97	0.55	1.76	1.11	0.56	1.97	1.24	0.57	2.16
	18	1.00	0.46	2.19	0.97	0.55	1.77	1.09	0.56	1.94	1.17	0.58	2.02	1.16	0.59	1.96
	21	0.99	0.47	2.10	1.08	0.56	1.94	1.14	0.58	1.98	1.10	0.59	1.84	1.10	0.61	1.81
	24	1.09	0.48	2.27	1.11	0.57	1.94	1.07	0.59	1.79	1.04	0.62	1.69	1.19	0.63	1.90
	1	0.02	0.10	0.18	-0.85	0.17	-4.96	-1.02	0.18	-5.57	-0.89	0.19	-4.59	-0.85	0.17	-4.93
	3	0.02	0.07	0.26	-0.63	0.13	-4.79	-0.69	0.16	-4.42	-0.62	0.17	-3.60	-0.67	0.16	-4.09
	6	0.05	0.05	0.98	-0.51	0.12	-4.32	-0.54	0.15	-3.66	-0.48	0.15	-3.23	-0.59	0.15	-3.80
	9	0.06	0.04	1.41	-0.40	0.11	-3.77	-0.43	0.12	-3.57	-0.48	0.14	-3.52	-0.58	0.16	-3.73
H-L	**12**	0.04	0.04	1.09	-0.37	0.09	-3.99	-0.44	0.11	-3.86	-0.49	0.13	-3.69	-0.62	0.15	-4.11
	15	0.04	0.03	1.18	-0.40	0.09	-4.40	-0.48	0.11	-4.29	-0.55	0.13	-4.29	-0.72	0.14	-5.13
	18	0.03	0.03	0.80	-0.43	0.09	-4.93	-0.50	0.11	-4.74	-0.61	0.12	-5.19	-0.69	0.14	-5.11
	21	0.03	0.03	0.94	-0.43	0.08	-5.34	-0.54	0.10	-5.52	-0.59	0.11	-5.16	-0.70	0.13	-5.29
	24	0.02	0.03	0.86	-0.43	0.08	-5.61	-0.53	0.10	-5.44	-0.60	0.11	-5.30	-0.72	0.13	-5.48

Table IV: Results for Big Firm H-L Portfolios Formed Using Firm-Specific Order Flow

Presented below are returns to a version of the Jegadeesh and Titman (1993) portfolio strategy, where instead of ranking on returns, large stocks are ranked on firm-specific order flow during the last one, three, six, nine or twelve months. Firm-specific order flow is the residual from a regression of total firm order-flow on market order flow. The group labeled High/(Low) are stocks in the highest/(lowest) quintile of order flow. The panel labeled H-L is the difference between the high and the low returns. This corresponds to the profits per dollar long to a zero-investment portfolio formed by taking a long position in the High group of stocks financed by an offsetting short position in the Low group of stocks.

		Ranking Period														
		One Month			Three Months			Six Months			Nine Months			Twelve Months		
Holding Period		Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t
	1	1.08	0.39	2.76	0.69	0.43	1.60	0.69	0.44	1.55	0.63	0.45	1.39	0.68	0.47	1.44
	3	1.07	0.39	2.70	0.77	0.44	1.76	0.70	0.45	1.56	0.74	0.46	1.60	0.70	0.48	1.46
	6	1.07	0.40	2.66	0.81	0.45	1.80	0.78	0.46	1.70	0.74	0.48	1.55	0.78	0.49	1.60
	9	1.05	0.41	2.54	0.85	0.46	1.84	0.76	0.47	1.59	0.80	0.49	1.63	0.73	0.50	1.47
High	12	1.06	0.42	2.50	0.82	0.47	1.73	0.81	0.49	1.67	0.75	0.50	1.49	0.84	0.51	1.63
	15	1.13	0.43	2.64	0.87	0.49	1.78	0.77	0.50	1.53	0.86	0.51	1.67	0.81	0.53	1.53
	18	1.19	0.44	2.70	0.84	0.50	1.67	0.89	0.51	1.73	0.84	0.53	1.58	0.77	0.55	1.41
	21	1.17	0.45	2.57	0.96	0.51	1.87	0.88	0.53	1.67	0.81	0.55	1.47	0.69	0.57	1.22
	24	1.24	0.46	2.67	0.95	0.53	1.81	0.85	0.55	1.55	0.73	0.57	1.28	0.71	0.58	1.21
	1	1.07	0.39	2.73	1.61	0.46	3.53	1.54	0.47	3.27	1.51	0.49	3.09	1.51	0.49	3.10
	3	1.01	0.39	2.60	1.43	0.45	3.18	1.36	0.47	2.90	1.40	0.48	2.92	1.43	0.49	2.94
	6	1.03	0.40	2.58	1.32	0.46	2.88	1.32	0.47	2.79	1.36	0.48	2.81	1.49	0.49	3.03
	9	1.01	0.41	2.47	1.32	0.47	2.83	1.31	0.48	2.71	1.44	0.49	2.93	1.47	0.50	2.94
Low	12	1.02	0.42	2.42	1.30	0.47	2.76	1.40	0.49	2.87	1.42	0.50	2.84	1.56	0.50	3.08
	15	1.10	0.43	2.56	1.37	0.48	2.84	1.37	0.50	2.76	1.53	0.51	3.01	1.54	0.52	2.95
	18	1.13	0.44	2.58	1.34	0.49	2.73	1.49	0.51	2.95	1.51	0.52	2.88	1.48	0.54	2.76
	21	1.11	0.45	2.46	1.46	0.50	2.91	1.46	0.52	2.81	1.46	0.54	2.70	1.41	0.56	2.54
	24	1.19	0.46	2.58	1.42	0.52	2.75	1.42	0.54	2.64	1.39	0.56	2.48	1.43	0.57	2.50
	1	0.02	0.08	0.21	-0.92	0.18	-5.03	-0.85	0.20	-4.33	-0.88	0.21	-4.23	-0.83	0.20	-4.22
	3	0.06	0.04	1.47	-0.66	0.16	-4.16	-0.66	0.18	-3.64	-0.66	0.18	-3.73	-0.73	0.18	-4.15
	6	0.04	0.03	1.45	-0.51	0.13	-3.82	-0.54	0.15	-3.51	-0.62	0.16	-3.90	-0.72	0.17	-4.32
	9	0.04	0.03	1.34	-0.47	0.12	-3.98	-0.55	0.14	-3.87	-0.65	0.15	-4.26	-0.74	0.16	-4.51
H-L	12	0.04	0.03	1.55	-0.48	0.10	-4.61	-0.59	0.13	-4.40	-0.67	0.14	-4.66	-0.72	0.16	-4.56
	15	0.04	0.03	1.35	-0.50	0.10	-5.03	-0.61	0.13	-4.81	-0.67	0.14	-4.84	-0.73	0.15	-4.84
	18	0.06	0.03	2.30	-0.50	0.09	-5.28	-0.60	0.12	-4.98	-0.67	0.13	-5.20	-0.71	0.15	-4.88
	21	0.05	0.03	2.04	-0.50	0.09	-5.46	-0.58	0.11	-5.24	-0.65	0.12	-5.23	-0.72	0.14	-4.99
	24	0.05	0.03	1.78	-0.47	0.08	-5.61	-0.57	0.11	-5.34	-0.66	0.12	-5.37	-0.72	0.14	-4.98

Table V: Alphas for the Big and Small Firm H-L Portfolios Formed Using Firm-Specific Order Flow

Presented below are estimated alphas relative to the CAPM, FF and Carhart models for the H-L zero investment portfolio for each ranking period/holding period combination. The portfolios are formed using firm-specific order flow. The alphas are computed by regressing the profits from the H-L zero investment portfolio on the excess market return and the three FF factors. Panel A presents the results for the H-L formed from large firms. Panel B presents the alphas for the H-L portfolio formed from small firms.

		Ranking Period														
		One Month			Three Months			Six Months			Nine Months			Twelve Months		
Model	Holding Period	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t
								Panel A: Large Firms								
	1	0.018	0.076	0.24	-0.934	0.186	-5.01	-0.872	0.200	-4.36	-0.881	0.210	-4.19	0.064	0.026	2.46
	3	0.060	0.038	1.57	-0.671	0.163	-4.13	-0.667	0.183	-3.63	-0.669	0.180	-3.71	-0.739	0.180	-4.12
	6	0.044	0.028	1.55	-0.517	0.136	-3.79	-0.545	0.157	-3.46	-0.631	0.163	-3.87	-0.723	0.170	-4.26
	9	0.037	0.028	1.36	-0.475	0.121	-3.94	-0.553	0.145	-3.82	-0.659	0.155	-4.25	-0.741	0.166	-4.46
CAPM	12	0.044	0.025	1.72	-0.486	0.106	-4.57	-0.596	0.136	-4.39	-0.683	0.147	-4.64	-0.724	0.161	-4.49
	15	0.044	0.027	1.65	-0.503	0.101	-4.96	-0.614	0.129	-4.76	-0.676	0.142	-4.77	-0.728	0.153	-4.75
	18	0.068	0.026	2.66	-0.503	0.097	-5.21	-0.603	0.123	-4.91	-0.677	0.132	-5.15	-0.715	0.149	-4.80
	21	0.064	0.026	2.46	-0.496	0.092	-5.37	-0.585	0.113	-5.18	-0.656	0.127	-5.17	-0.720	0.147	-4.91
	24	0.057	0.026	2.21	-0.474	0.085	-5.55	-0.580	0.109	-5.30	-0.666	0.125	-5.32	-0.721	0.146	-4.92
	1	0.060	0.078	0.77	-0.937	0.194	-4.84	-0.897	0.207	-4.34	-0.882	0.217	-4.06	0.061	0.027	2.31
	3	0.067	0.040	1.69	-0.685	0.169	-4.06	-0.686	0.190	-3.62	-0.657	0.186	-3.53	-0.763	0.185	-4.13
	6	0.049	0.029	1.65	-0.540	0.141	-3.84	-0.551	0.163	-3.39	-0.636	0.168	-3.79	-0.760	0.175	-4.35
	9	0.039	0.028	1.38	-0.484	0.125	-3.88	-0.557	0.149	-3.73	-0.680	0.160	-4.25	-0.774	0.171	-4.53
FF	12	0.043	0.026	1.62	-0.494	0.110	-4.50	-0.618	0.140	-4.41	-0.709	0.152	-4.68	-0.760	0.167	-4.54
	15	0.043	0.027	1.57	-0.526	0.105	-5.03	-0.643	0.133	-4.85	-0.711	0.147	-4.84	-0.775	0.159	-4.88
	18	0.067	0.026	2.54	-0.523	0.099	-5.25	-0.634	0.127	-4.99	-0.721	0.136	-5.30	-0.755	0.154	-4.89
	21	0.061	0.027	2.31	-0.521	0.096	-5.44	-0.623	0.117	-5.33	-0.693	0.131	-5.28	-0.751	0.152	-4.94
	24	0.056	0.027	2.10	-0.501	0.088	-5.68	-0.611	0.113	-5.40	-0.694	0.130	-5.36	-0.746	0.152	-4.90
	1	0.028	0.087	0.319	-0.912	0.210	-4.336	-0.772	0.225	-3.435	-0.828	0.239	-3.468	0.059	0.029	2.079
	3	0.037	0.043	0.863	-0.594	0.182	-3.265	-0.588	0.207	-2.845	-0.599	0.204	-2.931	-0.661	0.202	-3.273
	6	0.018	0.031	0.585	-0.453	0.153	-2.953	-0.503	0.179	-2.810	-0.557	0.183	-3.043	-0.664	0.188	-3.525
Carhart	9	0.023	0.031	0.753	-0.449	0.137	-3.280	-0.508	0.163	-3.123	-0.600	0.172	-3.482	-0.691	0.183	-3.769
	12	0.026	0.029	0.920	-0.448	0.120	-3.744	-0.558	0.151	-3.692	-0.642	0.163	-3.941	-0.680	0.178	-3.815
	15	0.030	0.030	1.016	-0.485	0.113	-4.297	-0.594	0.143	-4.168	-0.646	0.157	-4.112	-0.730	0.171	-4.274
	18	0.059	0.028	2.074	-0.483	0.107	-4.530	-0.577	0.136	-4.249	-0.678	0.146	-4.626	-0.746	0.169	-4.414
	21	0.059	0.029	2.079	-0.464	0.102	-4.541	-0.578	0.126	-4.585	-0.681	0.143	-4.744	-0.764	0.167	-4.565
	24	0.055	0.029	1.923	-0.454	0.095	-4.807	-0.590	0.124	-4.756	-0.697	0.142	-4.893	-0.770	0.168	-4.577
								Panel B: Small Firms								
	1	0.016	0.098	0.16	-0.834	0.174	-4.78	-1.024	0.185	-5.53	-0.898	0.197	-4.55	0.030	0.029	1.01
	3	0.013	0.066	0.20	-0.612	0.134	-4.58	-0.699	0.159	-4.39	-0.630	0.176	-3.57	-0.674	0.167	-4.05
	6	0.046	0.047	0.97	-0.507	0.121	-4.21	-0.537	0.149	-3.60	-0.479	0.152	-3.16	-0.594	0.158	-3.76
	9	0.059	0.040	1.49	-0.388	0.107	-3.63	-0.430	0.123	-3.50	-0.475	0.138	-3.45	-0.587	0.159	-3.69
CAPM	12	0.043	0.037	1.17	-0.357	0.093	-3.84	-0.438	0.116	-3.78	-0.498	0.137	-3.64	-0.631	0.155	-4.08
	15	0.041	0.032	1.27	-0.394	0.093	-4.26	-0.486	0.115	-4.22	-0.556	0.131	-4.24	-0.732	0.143	-5.12
	18	0.030	0.033	0.91	-0.428	0.088	-4.84	-0.503	0.108	-4.68	-0.617	0.120	-5.13	-0.705	0.138	-5.11
	21	0.030	0.029	1.01	-0.434	0.082	-5.30	-0.542	0.099	-5.46	-0.601	0.117	-5.14	-0.708	0.134	-5.28
	24	0.023	0.027	0.85	-0.442	0.079	-5.59	-0.532	0.099	-5.39	-0.605	0.114	-5.30	-0.731	0.133	-5.50
	1	-0.027	0.101	-0.27	-0.781	0.180	-4.35	-1.047	0.191	-5.49	-0.943	0.199	-4.74	0.026	0.030	0.87
	3	-0.012	0.068	-0.18	-0.610	0.138	-4.42	-0.746	0.162	-4.59	-0.697	0.178	-3.92	-0.732	0.170	-4.31
	6	0.033	0.049	0.67	-0.546	0.123	-4.44	-0.584	0.152	-3.84	-0.543	0.153	-3.55	-0.649	0.162	-4.01
	9	0.044	0.040	1.10	-0.433	0.108	-4.01	-0.471	0.125	-3.76	-0.528	0.141	-3.76	-0.627	0.164	-3.82
FF	12	0.027	0.037	0.73	-0.391	0.094	-4.14	-0.470	0.119	-3.94	-0.536	0.141	-3.81	-0.663	0.161	-4.12
	15	0.030	0.033	0.90	-0.433	0.094	-4.59	-0.512	0.119	-4.32	-0.594	0.135	-4.38	-0.760	0.149	-5.11
	18	0.021	0.033	0.62	-0.464	0.090	-5.17	-0.532	0.111	-4.79	-0.651	0.124	-5.26	-0.736	0.143	-5.15
	21	0.026	0.030	0.87	-0.469	0.083	-5.65	-0.573	0.102	-5.63	-0.635	0.120	-5.28	-0.735	0.139	-5.29
	24	0.019	0.028	0.66	-0.480	0.080	-6.03	-0.563	0.101	-5.57	-0.636	0.118	-5.39	-0.760	0.138	-5.50
	1	-0.067	0.110	-0.603	-0.929	0.198	-4.697	-1.072	0.208	-5.146	-0.963	0.221	-4.359	0.022	0.031	0.712
	3	-0.052	0.074	-0.698	-0.726	0.151	-4.821	-0.723	0.179	-4.042	-0.698	0.199	-3.509	-0.715	0.186	-3.839
	6	0.004	0.053	0.076	-0.545	0.136	-4.021	-0.563	0.170	-3.322	-0.535	0.169	-3.166	-0.668	0.172	-3.884
	9	0.029	0.045	0.651	-0.459	0.120	-3.812	-0.493	0.137	-3.604	-0.564	0.150	-3.767	-0.703	0.170	-4.139
Carhart	12	0.018	0.040	0.443	-0.424	0.103	-4.134	-0.517	0.126	-4.106	-0.613	0.146	-4.210	-0.742	0.165	-4.500
	15	0.023	0.035	0.673	-0.478	0.100	-4.783	-0.591	0.123	-4.810	-0.675	0.140	-4.842	-0.849	0.153	-5.534
	18	0.019	0.035	0.528	-0.508	0.094	-5.391	-0.589	0.116	-5.092	-0.728	0.129	-5.650	-0.813	0.152	-5.361
	21	0.022	0.031	0.712	-0.484	0.088	-5.513	-0.613	0.108	-5.686	-0.695	0.129	-5.383	-0.793	0.149	-5.338
	24	0.012	0.030	0.392	-0.483	0.085	-5.702	-0.596	0.109	-5.451	-0.684	0.127	-5.379	-0.804	0.148	-5.442

Table VI: Results for Big and Small Firm H-L Portfolios Formed Using Adjusted Firm-Specific Order Flow

Presented below are returns to a version of the Jegadeesh and Titman (1993) portfolio strategy, where instead of ranking on returns, large stocks are ranked on adjusted firm-specific order flow during the last one, three, six, nine or twelve months. Adjusted firm-specific order flow is computed by aggregating the residuals from a VAR(10) estimated on daily quote revisions and order flow to the monthly level. The monthly order flow for each firm is then regressed on the market order flow. The residual from this regression is adjusted firm-specific order flow. The group labeled High/(Low) are stocks in the highest/(lowest) quintile of order flow. The panel labeled H-L is the difference between the high and the low returns. This corresponds to the profits per dollar long to a zero-investment portfolio formed by taking a long position in the High group of stocks financed by an offsetting short position in the Low group of stocks.

	Ranking Period														
	One Month			**Three Months**			**Six Months**			**Nine Months**			**Twelve Months**		
Holding Period	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**	**Mean**	**S.E.**	**t**
							Panel A: Big Firms								
1	0.133	0.072	1.833	-0.762	0.175	-4.356	-0.566	0.187	-3.024	-0.648	0.190	-3.402	-0.669	0.192	-3.492
3	0.080	0.049	1.647	-0.473	0.150	-3.150	-0.411	0.168	-2.447	-0.449	0.174	-2.581	-0.556	0.172	-3.231
6	0.038	0.034	1.134	-0.385	0.126	-3.046	-0.369	0.153	-2.418	-0.474	0.161	-2.947	-0.543	0.165	-3.299
9	0.025	0.031	0.817	-0.342	0.116	-2.937	-0.384	0.138	-2.777	-0.487	0.154	-3.170	-0.550	0.160	-3.429
12	0.026	0.030	0.874	-0.399	0.104	-3.840	-0.438	0.130	-3.374	-0.527	0.146	-3.619	-0.570	0.155	-3.678
15	0.013	0.029	0.433	-0.416	0.099	-4.213	-0.458	0.124	-3.691	-0.527	0.141	-3.745	-0.560	0.148	-3.776
18	0.030	0.028	1.066	-0.415	0.096	-4.326	-0.456	0.120	-3.800	-0.511	0.133	-3.855	-0.563	0.147	-3.829
21	0.026	0.027	0.965	-0.411	0.093	-4.439	-0.438	0.113	-3.869	-0.503	0.130	-3.871	-0.588	0.144	-4.079
24	0.023	0.027	0.858	-0.380	0.087	-4.370	-0.434	0.112	-3.882	-0.527	0.128	-4.130	-0.591	0.144	-4.090
							Panel B: Small Firms								
1	-0.058	0.105	-0.549	-0.895	0.178	-5.029	-0.999	0.202	-4.954	-0.952	0.207	-4.593	-0.852	0.178	-4.796
3	-0.039	0.063	-0.624	-0.627	0.134	-4.666	-0.655	0.174	-3.767	-0.608	0.185	-3.285	-0.692	0.174	-3.978
6	0.049	0.043	1.143	-0.479	0.136	-3.531	-0.507	0.163	-3.116	-0.519	0.157	-3.304	-0.621	0.163	-3.809
9	0.056	0.037	1.524	-0.380	0.120	-3.162	-0.441	0.127	-3.469	-0.498	0.138	-3.596	-0.606	0.159	-3.803
12	0.041	0.034	1.180	-0.357	0.097	-3.688	-0.443	0.112	-3.971	-0.520	0.133	-3.917	-0.642	0.152	-4.233
15	0.036	0.032	1.145	-0.391	0.091	-4.319	-0.485	0.110	-4.424	-0.573	0.126	-4.549	-0.706	0.144	-4.915
18	0.021	0.031	0.681	-0.404	0.087	-4.659	-0.492	0.104	-4.739	-0.582	0.120	-4.854	-0.647	0.138	-4.684
21	0.028	0.029	0.974	-0.408	0.082	-4.985	-0.505	0.099	-5.098	-0.563	0.118	-4.784	-0.652	0.132	-4.943
24	0.023	0.026	0.860	-0.394	0.081	-4.894	-0.483	0.097	-4.970	-0.550	0.112	-4.935	-0.629	0.129	-4.861

Table VII: Alphas to H-L Portfolios Formed Using Adjusted Firm-Specific Order Flow

Presented below are estimated alphas relative to the CAPM, FF and Carhart models for the H-L zero investment portfolio for each ranking period/holding period combination. The portfolios are formed using adjusted firm-specific order flow. The alphas are computed by regressing the profits from the H-L zero investment portfolio on the excess market return and the three FF factors. Panel A presents the results for the H-L portfolio formed from large firms. Panel B presents the alphas for the H-L portfolio formed from small firms.

		Ranking Period														
		One Month			Three Months			Six Months			Nine Months			Twelve Months		
Model	Holding Period	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t	Mean	S.E.	t
								Panel A: Large Firms								
	1	0.131	0.074	1.778	-0.771	0.178	-4.331	-0.576	0.190	-3.032	-0.656	0.193	-3.391	0.031	0.028	1.102
	3	0.091	0.049	1.854	-0.475	0.153	-3.106	-0.413	0.171	-2.420	-0.452	0.177	-2.559	-0.565	0.175	-3.235
	6	0.044	0.034	1.310	-0.387	0.129	-3.011	-0.372	0.155	-2.397	-0.480	0.163	-2.940	-0.552	0.168	-3.294
	9	0.026	0.032	0.837	-0.345	0.118	-2.918	-0.389	0.140	-2.770	-0.498	0.156	-3.184	-0.560	0.163	-3.432
CAPM	12	0.029	0.030	0.969	-0.402	0.106	-3.808	-0.447	0.132	-3.381	-0.538	0.148	-3.623	-0.577	0.158	-3.648
	15	0.016	0.030	0.547	-0.415	0.101	-4.121	-0.463	0.127	-3.656	-0.530	0.143	-3.695	-0.566	0.151	-3.734
	18	0.033	0.028	1.188	-0.413	0.098	-4.217	-0.458	0.122	-3.748	-0.515	0.135	-3.806	-0.565	0.150	-3.768
	21	0.031	0.028	1.102	-0.407	0.094	-4.310	-0.442	0.116	-3.826	-0.504	0.132	-3.805	-0.586	0.147	-4.000
	24	0.028	0.028	1.020	-0.378	0.089	-4.254	-0.439	0.114	-3.855	-0.527	0.130	-4.060	-0.590	0.147	-4.023
	1	0.126	0.077	1.650	-0.792	0.185	-4.288	-0.593	0.197	-3.009	-0.649	0.199	-3.255	0.033	0.029	1.136
	3	0.088	0.051	1.737	-0.492	0.157	-3.126	-0.421	0.176	-2.394	-0.441	0.181	-2.432	-0.574	0.180	-3.191
	6	0.048	0.035	1.361	-0.404	0.132	-3.056	-0.365	0.160	-2.288	-0.480	0.168	-2.857	-0.577	0.173	-3.336
	9	0.031	0.033	0.946	-0.344	0.122	-2.825	-0.382	0.144	-2.648	-0.507	0.161	-3.148	-0.585	0.168	-3.483
FF	12	0.029	0.031	0.947	-0.398	0.108	-3.676	-0.455	0.136	-3.341	-0.552	0.153	-3.617	-0.606	0.164	-3.699
	15	0.017	0.031	0.545	-0.423	0.104	-4.081	-0.474	0.131	-3.628	-0.550	0.149	-3.699	-0.607	0.157	-3.863
	18	0.035	0.029	1.198	-0.420	0.101	-4.152	-0.472	0.127	-3.717	-0.545	0.141	-3.872	-0.601	0.155	-3.873
	21	0.033	0.029	1.136	-0.416	0.098	-4.241	-0.463	0.120	-3.847	-0.528	0.138	-3.838	-0.615	0.152	-4.046
	24	0.033	0.029	1.141	-0.392	0.093	-4.234	-0.458	0.118	-3.868	-0.545	0.135	-4.045	-0.616	0.152	-4.039
	1	0.169	0.084	2.025	-0.798	0.199	-4.012	-0.475	0.213	-2.229	-0.638	0.220	-2.899	0.021	0.030	0.679
	3	0.087	0.055	1.574	-0.452	0.171	-2.643	-0.369	0.192	-1.919	-0.408	0.201	-2.034	-0.498	0.197	-2.534
	6	0.036	0.038	0.932	-0.376	0.145	-2.596	-0.359	0.176	-2.040	-0.425	0.184	-2.317	-0.491	0.186	-2.636
	9	0.029	0.036	0.806	-0.357	0.134	-2.666	-0.353	0.158	-2.242	-0.453	0.174	-2.610	-0.501	0.180	-2.783
Carhart	12	0.032	0.034	0.931	-0.388	0.118	-3.274	-0.416	0.147	-2.833	-0.496	0.164	-3.030	-0.520	0.175	-2.979
	15	0.011	0.033	0.344	-0.408	0.111	-3.659	-0.439	0.139	-3.158	-0.493	0.158	-3.114	-0.556	0.169	-3.291
	18	0.023	0.031	0.751	-0.398	0.107	-3.712	-0.431	0.134	-3.203	-0.512	0.151	-3.399	-0.588	0.169	-3.470
	21	0.021	0.030	0.679	-0.382	0.103	-3.699	-0.439	0.128	-3.437	-0.530	0.149	-3.559	-0.630	0.166	-3.792
	24	0.023	0.030	0.760	-0.381	0.097	-3.905	-0.464	0.127	-3.650	-0.567	0.146	-3.878	-0.645	0.167	-3.869
								Panel B: Small Firms								
	1	-0.072	0.106	-0.675	-0.867	0.180	-4.814	-1.011	0.205	-4.934	-0.945	0.211	-4.489	0.026	0.029	0.891
	3	-0.046	0.064	-0.728	-0.615	0.137	-4.502	-0.666	0.177	-3.766	-0.609	0.188	-3.241	-0.694	0.177	-3.930
	6	0.047	0.044	1.072	-0.479	0.138	-3.474	-0.511	0.165	-3.089	-0.510	0.159	-3.199	-0.619	0.166	-3.723
	9	0.056	0.038	1.496	-0.374	0.122	-3.058	-0.437	0.129	-3.382	-0.487	0.141	-3.458	-0.599	0.162	-3.689
CAPM	12	0.039	0.035	1.120	-0.348	0.098	-3.542	-0.441	0.114	-3.875	-0.509	0.135	-3.768	-0.633	0.155	-4.098
	15	0.035	0.032	1.101	-0.386	0.092	-4.189	-0.484	0.112	-4.332	-0.563	0.128	-4.391	-0.696	0.147	-4.747
	18	0.021	0.032	0.666	-0.399	0.088	-4.519	-0.489	0.106	-4.619	-0.571	0.122	-4.668	-0.638	0.141	-4.541
	21	0.026	0.029	0.891	-0.404	0.083	-4.847	-0.503	0.101	-4.972	-0.553	0.120	-4.622	-0.644	0.134	-4.809
	24	0.018	0.027	0.668	-0.392	0.082	-4.765	-0.481	0.099	-4.858	-0.542	0.113	-4.796	-0.625	0.131	-4.758
	1	-0.107	0.110	-0.967	-0.859	0.187	-4.605	-1.030	0.212	-4.860	-0.976	0.214	-4.563	0.026	0.030	0.873
	3	-0.052	0.066	-0.792	-0.656	0.139	-4.706	-0.722	0.180	-4.022	-0.677	0.189	-3.583	-0.767	0.178	-4.300
	6	0.047	0.045	1.039	-0.527	0.140	-3.764	-0.569	0.167	-3.399	-0.578	0.160	-3.616	-0.694	0.168	-4.123
	9	0.054	0.039	1.406	-0.424	0.122	-3.466	-0.494	0.130	-3.802	-0.558	0.142	-3.936	-0.663	0.165	-4.009
FF	12	0.040	0.036	1.094	-0.390	0.099	-3.944	-0.488	0.116	-4.219	-0.565	0.137	-4.124	-0.692	0.159	-4.359
	15	0.038	0.033	1.143	-0.430	0.093	-4.621	-0.527	0.114	-4.627	-0.618	0.131	-4.712	-0.750	0.151	-4.968
	18	0.022	0.033	0.661	-0.437	0.089	-4.894	-0.531	0.108	-4.899	-0.624	0.125	-4.994	-0.687	0.145	-4.752
	21	0.026	0.030	0.873	-0.442	0.084	-5.247	-0.547	0.103	-5.312	-0.606	0.122	-4.987	-0.693	0.137	-5.043
	24	0.013	0.028	0.482	-0.440	0.082	-5.352	-0.528	0.100	-5.271	-0.598	0.114	-5.228	-0.680	0.134	-5.061
	1	-0.111	0.121	-0.92	-1.006	0.2024	-4.973	-1.059	0.232	-4.575	-1.031	0.238	-4.339	0.0235	0.032	0.73
	3	-0.068	0.072	-0.95	-0.725	0.1529	-4.738	-0.687	0.2	-3.442	-0.702	0.212	-3.304	-0.741	0.198	-3.748
	6	0.0213	0.049	0.434	-0.494	0.1551	-3.184	-0.545	0.188	-2.894	-0.557	0.179	-3.117	-0.683	0.182	-3.748
	9	0.0594	0.043	1.394	-0.42	0.1381	-3.043	-0.474	0.145	-3.267	-0.544	0.155	-3.513	-0.702	0.176	-3.99
Carhart	12	0.0339	0.04	0.852	-0.39	0.1094	-3.561	-0.475	0.126	-3.774	-0.588	0.147	-3.999	-0.741	0.167	-4.434
	15	0.0316	0.036	0.879	-0.429	0.1009	-4.254	-0.547	0.122	-4.477	-0.644	0.14	-4.6	-0.81	0.16	-5.075
	18	0.0223	0.035	0.636	-0.454	0.0965	-4.701	-0.542	0.116	-4.656	-0.644	0.135	-4.777	-0.731	0.157	-4.671
	21	0.0235	0.032	0.73	-0.43	0.0916	-4.695	-0.534	0.112	-4.772	-0.601	0.134	-4.475	-0.712	0.15	-4.759
	24	0.0085	0.03	0.284	-0.398	0.0903	-4.41	-0.498	0.111	-4.493	-0.577	0.127	-4.547	-0.675	0.146	-4.611