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ABSTRACT

Individual Investor Trading and Return Patterns around Earnings Announcements*

This paper documents evidence consistent with informed trading by individual investors around earnings announcements using a unique dataset of NYSE stocks. We show that intense aggregate individual investor buying (selling) predicts large positive (negative) abnormal returns on and after earnings announcement dates. We decompose the abnormal returns into a component that is attributed to risk-averse liquidity provision and a component that is attributed to private information or skill, and show that about half of the abnormal returns in the three months following the event can be attributed to private information. We also examine the behavior of individuals after the earnings announcement and find that they trade in the opposite direction to both pre-event returns (i.e., exhibit "contrarian" behavior) and the earnings surprise (i.e., exhibit "news-contrarian" behavior). The latter behavior, which could be consistent with profit-taking, has the potential to slow down the adjustment of prices to earnings news and contribute to the post-earnings announcement drift.

JEL Classification: G11 and G14
Keywords: earnings announcement and individual investors

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I. Introduction

Individual investors are often portrayed in the behavioral finance literature as unsophisticated "noise" traders who are subject to fads and psychological biases. Rarely is the question asked whether individuals gain by trading on private information or possess skill in interpreting public information. This is an important question that has added relevance in light of the recent interest in theoretical models where managers learn from prices (in contrast to the old paradigm where managers have better information than outsiders) and therefore financial markets affect the real economy.[1]

The potential information advantage of individuals may seem counter-intuitive given the vast resources institutions devote to gathering information, but there are nonetheless reasons to explore the information content of the trades of individual investors. First, even if each individual investor has very imprecise information, when the information is aggregated through the trades of many individuals, the resulting signal can be relatively precise. Second, individuals may be better positioned to trade aggressively when they are informed, because it is easier to buy or sell small quantities of shares, and individuals may also be less constrained than a typical institution (at least with respect to diversification requirements or short-selling).

To examine the information content of trading by individual investors, this paper focuses on their trades around earnings announcements. Since the purpose of an earnings announcement is the release of information to the market, we expect that informed individuals should be especially active at these times. Indeed, if institutions are averse to trading too aggressively immediately before such events for fear of litigation, informed individuals may have advantages relative to informed institutions.

Our evidence indicates that pre-event trading by individuals does in fact predict the returns on and after earnings announcement dates. We find that stocks that individuals accumulated in the ten days prior to the earnings announcement exhibit abnormal returns that exceed the abnormal returns of stocks they sold by about 1.47% in

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[1] See, for example, Dow and Gorton (1997), Subrahmanyam and Titman (1999, 2001), Dow and Rahi (2003), Foucault and Gehrig (2008), and Dow, Goldstein, and Guembel (2010).

the two-day event window around earnings announcements. Moreover, we find a 5.45% average difference in the returns of these stocks in the three months after the event. These results, which are statistically very significant, are consistent with the idea that in aggregate, individual investor trading prior to earnings announcements conveys pertinent information.

The results in this paper should be contrasted with prior research by Kaniel, Saar, and Titman (2008) (hereafter KST) which, using the same data, also found evidence of a positive relation between individual trading and stock returns. However, KST examined the unconditional relationship between individual trading and returns, and found fairly modest abnormal returns that they attributed to the liquidity provision role of individual investors. One interpretation of the stronger results found in this paper is that institutions have a greater need for liquidity around earnings announcement dates because of the higher level of uncertainty, and that this greater demand for liquidity creates the greater profit opportunities for individuals who provide liquidity around these dates.

To gauge the determinants of the much stronger return patterns around earnings announcement dates we develop a methodology that decomposes the cumulative abnormal returns following the buying and selling of individuals into a component that is attributed to liquidity provision and a component that is attributed to trading on private information or skill. Based on assumptions we detail later in the paper, we conclude that liquidity provision explains roughly half of the abnormal return associated with the trading of individuals prior to the earnings announcement, with the rest being attributable to private information. Consistent with our priors, we find that the information component is especially strong for smaller firms, where it is reasonable to assume that individuals have insights that sell-side analysts or institutional investors in general do not possess. We also study individual investor trading around dividend announcements and find further evidence consistent with informed trading by individuals.

We are, of course, not the first to examine the behavior of individual investors around earnings announcements; however, the evidence we document of informed trading by individuals in the U.S. around these events is novel. Our investigation benefits from the use of a large dataset that contains about 1.55 trillion dollars of individual investor trading in all NYSE stocks over four years, 2000-2003. On this dimension, our research extends prior literature that either indirectly infers the trades of individuals based on trade size or looks at a small subset of the market.[2] Welker and Sparks (2001), for example, use the much smaller NYSE's TORQ dataset to look at individual and institutional trading around public announcements, but do not find a relation between individual trading prior to the event and subsequent returns. After conducting tests to reconcile our results with theirs, we believe that the source of the difference resides in lack of power to uncover the patterns due to the small sample size in TORQ (144 securities over a 3 month period).

Outside the U.S., Vieru, Perttunen, and Schadewitz (2006) present evidence from Finland that net trading by very active individual traders in the three days prior to earnings announcements is positively related to abnormal returns in the five days that start on the event day (though this results does not hold for all other individuals). While consistent with our findings, it is unclear whether this predictive relation reflects trading on private information because their tests do not separate the compensation for liquidity provision.

In addition to examining pre-announcement trading and showing how it relates to announcement and post-announcement returns, we study how individuals trade following the earnings announcement. We find that in the post-announcement period individuals tend to trade in the opposite direction to pre-event returns (i.e., they exhibit "return-contrarian" behavior), as well as to the direction of the earnings surprise (i.e., they exhibit "news-contrarian" behavior). The "news-contrarian" behavior of individuals is consistent with the idea that individuals are responsible (at least in part) for the post-earnings announcement drift, and contrasts somewhat with the conclusions of Hirshleifer, Myers,

[2] Many results concerning individual investor trading in the U.S. were established using a smaller sample containing 24.3 billion dollars of trading by clients of one discount broker from 1991 through 1996. Other papers utilized the TORQ dataset that contains three months of data at the end of 1990 for 144 securities. Some papers also used small trades as a proxy for the trading of individual investors. Research using recent data, however, casts doubt on the usefulness of this methodology and even suggests that smaller traders are more likely to come from institutions rather than individuals (See, for example, Hvidkjaer (2005), and Campbell, Ramadorai, and Schwartz (2009)).

Myers, and Teoh (2008) who investigate this issue by looking at the behavior of clients of one discount broker.[3] Although trading in the opposite direction to the drift may slow down the price adjustment process and may not, in isolation, be a good strategy, it is not necessarily an indication of irrational trading. Our findings on individual trading before and after the events may suggest that individuals could be profitably reversing positions to which they have entered before the announcements.

The rest of this paper proceeds as follows. The next section describes the sample and the comprehensive dataset we use. Section III documents the relation between pre-event net individual investor trading and subsequent returns, and proceeds to apply the decomposition methodology to investigate our main research question about the potential for informed trading. Section IV examines the behavior of individuals after earnings announcements. Section V discusses the most related papers in the literature, and Section VI concludes.

II. Sample and Data

II.A. NYSE Trading Data

We study the trading of individuals around earnings announcements using a comprehensive dataset that contains four years (2000-2003) of daily buy and sell volume of executed orders for a large cross section of NYSE stocks. The dataset was constructed from the NYSE's Consolidated Equity Audit Trail Data (CAUD) files that contain all orders that execute on the exchange. The CAUD files include a field called Account Type that specifies for each order whether it originates from an individual investor.

Account Type is a mandatory field a broker has to fill for each order that is sent to the NYSE. The Account Type field is not audited by the NYSE on an order-by-order basis, but NYSE officials monitor the use of this field by brokers. In particular, any abnormal use of the individual investor designation in the Account Type field by a

[3] The drift was first described in Ball and Brown (1968). See also Foster, Olsen, and Shevlin (1984) and Bernard and Thomas (1989, 1990).

brokerage firm is likely to draw attention, which prevents abuse of the reporting system. We therefore believe that the Account Type designation of orders is fairly accurate.[4]

An important advantage of our dataset is that the information about daily buy and sell volume of individual investors was created by aggregating executed *orders* rather than trades. In other words, the classification into buy and sell volume in our dataset is exact and we do not have to rely on classification algorithms such as the one proposed by Lee and Ready (1991).

We start our construction of a daily abnormal net individual trading series by computing an imbalance measure: subtracting the value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year.[5] We then subtract the daily average of that imbalance measure over the sample period to get an abnormal net individual trading measure, which we believe is more suitable for examining the patterns of trading around earnings announcements.[6] Specifically, we define $IndNT_{i,t}$ for stock i on day t as:

$$IndNT_{i,t} = \text{Individual Imbalance}_{i,t} - \frac{1}{T} \sum_{\text{all days in 2000-2003}} \text{Individual Imbalance}_{i,t}$$

where,

$$\text{Individual Imbalance}_{i,t} = \frac{\text{Individual buy dollar volume}_{i,t} - \text{Individual sell dollar volume}_{i,t}}{\text{Average daily dollar volume in the calendar year}_{i,t}}$$

We define cumulative abnormal net individual trading over a certain period, *[t,T], as:*

$$IndNT^{i}_{[t,T]} = \sum_{k=t}^{T} IndNT_{i,k}$$

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[4] Additional information on the Account Type field (and the reporting of individual investor trading) can be found in Lee and Radhakrishna (2000) and Kaniel, Saar, and Titman (2008).

[5] Kaniel, Saar, and Titman (2008) note that some trading in NYSE-listed stocks does not take place on the NYSE. For example, some brokers either sell some of their retail order flow to wholesalers for execution or internalize a certain portion of their clients' orders by trading as principal against them. During this sample period, these trades took place on one of the regional exchanges (or alternatively were reported to the NASD) and are therefore not in our sample of NYSE executions. However, these brokers still send a certain portion of their retail order flow to the NYSE, and are more likely to send those orders that create an imbalance not easily matched internally. Therefore, Kaniel, Saar, and Titman argue that net individual trading (i.e., imbalances in individuals' executed orders on the NYSE) probably reflects, even if not perfectly, the individuals' imbalances in the market as a whole.

[6] We also repeated the analysis with a measure constructed by subtracting the cross-sectional average of the individuals' imbalances each day instead of subtracting the time-series average for the same stock over the sample period. The results of this analysis were similar to our findings with the time-series adjustment.

where the period is defined relative to the earnings announcement date (day zero). For example, $IndNT_{[-10,-1]}$ is cumulative abnormal net individual trading from ten days prior to the earnings announcement to one day prior to the announcement.

II.B. Sample

Our sample contains all common, domestic stocks that were traded on the NYSE any time between January 1, 2000 and December 31, 2003. We use the CRSP database to construct the sample, and match the stocks to the NYSE dataset of individual trading by means of ticker symbol and CUSIP. This procedure results in a sample of 2,034 stocks. We then use IBES and COMPUSTAT to identify all the dates where stocks in our sample had earnings announcements, and impose two restrictions on the sample.[7] First, we require 60 days of data prior to and after the announcements, which eliminates most announcements from the first (and last) three months of the sample period. Second, in order to compute our analysts' earnings surprise measure we require that there is an observation in the IBES database for the mean analysts' forecast in the month prior to the earnings announcement (i.e., at least one analyst with an earnings forecast), and also information about the actual earnings number.

Our screens result in a final sample of 1,821 stocks with 17,564 earnings announcement events. Panel A of Table 1 presents summary statistics from CRSP on the sample stocks (for the entire sample and for three size groups). Panel B of Table 1 reports the number of events in each month of the sample period. Table 2 looks at net individual trading around earnings announcements. We observe that individuals buy stocks in the two-week period prior to earnings announcements. At the time of the event itself (days [0,1]) individuals sell, and we observe continued selling in the week after the event.

It is interesting to note that the pattern we observe in Table 2 concerning the trading of individuals on and after earnings announcements differs from the pattern documented by papers that utilize small trades as a proxy for individual investor trading. Lee (1992) and Frazzini and Lamont (2006) find net small trade buying on the

[7] For each stock on each quarter, we compare the announcement dates from IBES (the REPDATS field) and COMPUSTAT (the RDQE filed) and choose the earlier one if they are different.

announcement date and in the immediate aftermath of the event, which they argue is consistent with the "attention-grabbing" hypothesis, i.e., that individuals are more likely to initiate purchases of stocks that grab their attention (e.g., due to an earnings announcement). While using small trades as a proxy for the trades of individual investors was shown to be reasonable for a 1990 sample of NYSE stocks (Lee and Radhakrishna (2000)), recent research casts doubt on its usefulness. For example, Campbell, Ramadorai, and Schwartz (2008) look at how trades of different sizes relate to changes in institutional holdings from 1993 through 2000 and conclude that the smallest trades (below $2,000) are more likely to come from institutions rather than individuals.[8]

Since we actually observe the trading of individual investors and find that individuals are net sellers at the time of the announcement and several days following the event, it is indeed possible to that the different small trade pattern is due to the fact that institutions break up their orders and therefore small trades may come from institutions rather than from individuals. This evidence highlights the advantage of investigating trading around earnings announcements using our dataset that directly identifies the trading of individuals.

II.C. Abnormal Returns and Earnings Surprises

Throughout the paper we define abnormal returns as market-adjusted returns and use the equal-weighted portfolio of all stocks in the sample as a proxy for the market portfolio.[9] To create the cumulative return of the market portfolio, say over a 60-day period, we first compute for each stock the cumulative (raw) return over the relevant 60-day period. The average of these returns across the stocks in the sample is what we define as the return on the equal-weighted market portfolio. Our definition of cumulative abnormal returns for stock i in period $[t, T]$, $CAR_{i,[t,T]}$, is the cumulative return on stock i minus the cumulative

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[8] Hvidkjaer (2008), who investigates the relation between small trade volume and stock returns, also notes that small trade volume increases markedly in the final years of his sample (that ends in 2004), and it no longer seems to be negatively related to changes in institutional holdings. The bulk of the increase in small trades is probably coming from institutions that split the positions they want to trade into small orders.

[9] Our results are robust to using the value-weighted portfolio of the stocks in our sample as a proxy for the market portfolio.

return on the market proxy (for period *[t,T]*). Our results are robust to the use of size-adjusted returns as an alternative definition of abnormal returns.

Our investigation focuses both on the relation between individual investor trading and returns around earnings announcements and on how individuals react to good and bad news. Therefore, we require a measure of earnings surprise (or the news component of the earnings announcement), and use analysts' forecasts to define that surprise. More specifically, we define the normalized earnings surprise, ES, as the actual earnings minus the earnings forecast, divided by the price on the forecast day. The earnings forecast is the mean of analysts' forecast one month before the earnings announcements. An earnings surprise measure using analysts' forecasts is rather standard in the literature, but we certainly acknowledge that it is just a proxy for the surprise. There are also papers that use the abnormal return at the time of the earnings announcement as a proxy for the surprise, and each measure has its own advantages and disadvantages.[10] In our regression analysis explaining post-event individual investor trading we include, in addition to the analysts' earnings surprise measure, the abnormal return at the time of the announcement as an additional proxy for the news content of the announcement.

III. Individual Trading and Return Predictability: Information vs. Liquidity

III.A. Pre-Event Individual Trading and Abnormal Returns

As a first step, we document the relation between the trading of individuals prior to the earnings announcement and the returns of those stocks they intensely buy or sell. We first sort all stocks each quarter according to our net individual investor trading measure in the 10 trading days (two weeks) before the event and put the stocks in five categories (quintile 1 contains the stocks that individuals sold the most and quintile 5 contains the

[10] The analysts' earnings surprise measure presumably reflects the surprise relative to the opinions of well-informed, sophisticated investors. It has the advantage that it does not involve the price level or return at the time of the event that can be affected by liquidity shocks unrelated to the actual updating of beliefs about the stock. On the other hand, it is perfectly conceivable that investors other than sell-side analysts (e.g., skillful individuals, hedge funds, and proprietary trading desks) have information that is relevant to the pricing of the stock that sell-side analysts do not possess. As such, the return at the time of the announcement would aggregate everyone's opinion, leading to a better measure of surprise than the one that solely considers the information set of the sell-side analysts.

stocks individuals bought the most). We compute for each stock the cumulative market-adjusted return for the announcement window (days [0,1]) and several periods (up to 60 days) following the announcement.[11] We then examine the mean market-adjusted abnormal returns of the stock-quarters in each of the different quintiles, correcting for the possible effects of clustering using the Fuller-Battese methodology (see Fuller and Battese (1974)). Specifically, for each quintile we model the cumulative abnormal return using a one-way random effect framework in which there is a weekly effect (for periods [0,1] and [2,6]), a monthly effect (for periods [2,11] and [2,21]), or a quarterly effect (for periods [2,61] and [0,61]).[12]

Panel A of Table 3 shows that the stocks that individuals intensely bought in the two weeks before the announcements outperform those that they intensely sold, on average, by 1.47% during the event window (days [0,1]), and they continue to outperform in the three months following the event for a total of 5.45% (over the period [0,61]). The abnormal returns can be attributed to both buying and selling by individuals: stocks that individuals intensely sold (quintile 1) experience a negative abnormal return of -0.66% on the event and -3.38% over the [0,61] period, while those they intensely bought (quintile 5) have a 0.78% abnormal return in the event window and a 2.15% abnormal return up to day 61.[13]

We also sort the stocks according to size and repeat the analysis separately for three market-capitalization groups: small, mid-cap, and large stocks.[14] For this analysis, we compute abnormal returns for a stock by subtracting from it the return of the equal-weighted portfolio of all stocks in its group (rather than the entire market). Panel B of Table 3 shows that the difference in the abnormal return after three months ([0,61]) between quintile 5 (the stocks that individuals bought) and quintile 1 (the stocks that

[11] We use sixty days starting two days after the announcement as the length of our post-event period to be consistent with the literature that examines the post-earnings announcement drift.
[12] Similar results are obtained if we use quarterly clustering for all periods, or if we utilize a simple adjustment for clustering rather than the Fuller-Battese methodology (i.e., taking the mean of each period as a single observation without adjusting for the precision of the mean estimate).
[13] We find a similar pattern when we sort on net individual trading in the 20 days prior to the announcement.
[14] We sort stocks into deciles by market capitalization and define small stocks as those in deciles 1, 2, 3, and 4, mid-cap stocks as those in deciles 5, 6, and 7, and large stocks as those in deciles 8, 9, and 10.

individuals sold) is highly significant in all three size groups: 8.03% for small stocks, 3.51% for mid-cap stocks, and 3.03% for large stocks.

To summarize the results in Table 3, we observe that pre-event trading by individuals is significantly related to abnormal returns at the time of the event and over the 60-day period following the announcement. Before proceeding to decompose the abnormal returns, we carry out a couple of robustness tests to ensure that this predictive relation is not simply a transformation of the return mean-reversion phenomenon or the earnings surprise.

The first test is motivated by the literature that documents short-term return reversals (e.g., Jegadeesh (1990, Lehmann (1990)). If individuals trade in a contrarian manner, (as shown in Kaniel, Saar, and Titman (2008)), our results in Table 3 can potentially be driven by return reversals rather than past individual trading. To examine this possibility, in Panel A of Table 4 we sort earnings announcements each quarter into five quintiles according to the cumulative market-adjusted return in [-10,-1], and within each quintile we sort into five quintiles on net individual trading before the event ($IndNT_{[-10,-1]}$). We then examine the cumulative abnormal returns over the period [0,61]. The bottom row of the table shows that conditioning on net individual trading matters a lot within each past return quintile. Looking at the last column of the table, however, suggests that past return does not seem to matter much, indicating that mean reversion does not explain the return pattern we document.

In Panel B of Table 4 we condition first on the nature of the earnings news and then on pre-event individual trading. We sort the stocks each quarter into quintiles according to the analysts' earnings surprise measure (ES), where quintile 1 is the most negative surprise and quintile 5 the most positive surprise, and then within each ES quintile we sort on net individual trading before the event ($IndNT_{[-10,-1]}$), where quintile 1 are those stocks individuals sold the most in the 10 days prior to the announcement and quintile 5 are those they bought the most over that period. We then examine the cumulative market-adjusted returns over the period [0,61].

We observe that both pre-event individual trading and the nature of the earnings surprise seem to matter for the cumulative abnormal returns. This can be observed most clearly by looking at the bottom row of the table (the difference between quintile 5 and quintile 1 of net individual trading) and the last column of the table (the difference between quintile 5 and quintile 1 of the earnings surprise measure). Among stocks with negative news, we find that stocks that individuals intensely sold before the event experience a very negative subsequent abnormal return (-7.46%) over the period [0,61], but stocks that individuals bought before the event do not go down significantly. Similarly, among stocks with positive news, we find that stocks that individuals bought before the event have a very positive abnormal return (7.32%), but those that individuals sold do not go up significantly.

Our last test employs a regression framework that enables us to implement multiple controls in a single model. We run regressions that investigate the predictive power of net individual trading prior to the event while controlling for past returns (from Panel A of Table 4) and the earnings surprise (from Panel B of Table 4). The dependent variable in the regressions is the cumulative abnormal return on and after the announcements ($CAR_{[0,61]}$). For robustness, we use models where pre-event abnormal returns and net individual trading are measured over either 10 days or 60 days before the announcements.[15] To control for earnings news, we sort the earnings announcements each quarter into five quintiles according to the analysts' earnings surprise measure, and use dummy variables for these quintiles in the regression.

Table 5 presents the results of the regression analysis with clustering-corrected t-statistics for the coefficients.[16] We observe that the dummy variable for ES1 (the quintile of the most negative surprises) has a negative and significant coefficient, while the

[15] The reason we consider both specifications is that while in Table 3 and Table 4 we focus on net investor trading in the 10 days before the event, our choice for a three-month post-event period follows other papers in the "drift" literature, and therefore we also look at a pre-event period of 60 days to have equal periods before and after the announcements.

[16] As in the other tables, we implement the Fuller-Battese methodology in order to overcome the potential econometric problems associated with contemporaneously correlated errors for earnings announcements that are clustered in time. We repeated the regressions with an alternative methodology in the spirit of Fama and MacBeth (1973) that is also meant to overcome the potential problem of contemporaneously correlated errors. The results were similar.

dummy variable for ES5 (the quintile of the most positive surprises) has a positive and significant coefficient. These coefficients reflect both the impact of the earnings surprise on prices and the "drift" phenomenon (because the dependent variable is $CAR_{[0,61]}$). Most importantly, we observe that net individual trading before earnings announcements is a strong predictor of the cumulative abnormal return in [0,61]. The positive and highly significant coefficient on net individual trading means that more intense individual buying (selling) before the earnings announcement is associated with higher (lower) market-adjusted abnormal returns on and after the event.[17] We carried out sub-period analysis by running these regressions separately for each of the four calendar years in our sample period, and found a similar statistically significant effect in all sub-periods.

III.B. Decomposition of the Abnormal Return: Methodology

The analysis in Section III.A reveals that net individual trading prior to earnings announcements predicts cumulative abnormal returns on and after the event. The magnitude of the returns we document is large, and the effect is both robust and interesting.

Theoretical models provide two possible explanations for these return patterns. First, these patterns could indicate that individuals have useful information (either private information or skill in interpreting public information) about the implications of forthcoming earnings announcements. While this is probably the most straightforward explanation of the abnormal returns, it contrasts with the usual tendency to attribute private information or skill to sophisticated institutional investors rather than to individuals. Of course, this interpretation does not require that each individual is particularly well informed. Rather, it is possible that some individual investors have very small pieces of the puzzle and that by aggregating their net trading we in effect create a relatively precise signal that predicts future returns.

The second explanation is that these return patterns arise when risk-averse individuals provide liquidity to other traders (e.g., institutions) that may have an incentive

[17] We also ran models adding a control variable for post-event net individual trading to account for a potential trading-induced price pressure after the event. The coefficient on pre-event net individual trading was positive and highly statistically significant in all specifications.

to change positions prior to earnings announcements. Theoretical models such as Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993) demonstrate that when certain traders require immediacy, they must offer price concessions to induce risk-averse investors (in our case, individuals) to take the other side of their trades. Since there is no change in the expected future cash flows of the assets, these price concessions result in subsequent return reversals. For example, if net individual buying before earnings announcements accommodates the urgent selling of other investors who demand immediacy, prices would go down before the events, offering buyers abnormal returns following the event, which is exactly the pattern we document. A symmetrical pattern arises when individual investor selling accommodates demand for liquidity from buyers prior to the announcement, in which case we subsequently document strong negative abnormal returns.

Kaniel, Saar, and Titman (2008), who look at weeks with intense buying and selling by individuals using the same NYSE dataset, find evidence that they interpret as providing support for the risk-averse liquidity provision models. Specifically, they find cumulative abnormal returns of -0.5% (0.8%) in the two to three months after a week of intense selling (buying) by individuals, which are considerably smaller in magnitude than the returns we find around earnings announcements.[18] In the analysis that follows, we provide further tests to better understand whether the higher returns we document around earnings announcements arise because of the information that individuals possess or because the greater liquidity demand around earnings announcements increases the total compensation that liquidity providers earn.[19]

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[18] The patterns in abnormal returns they found were robust to eliminating stock/weeks with dividend or earnings announcements.

[19] At the suggestion of the referee, we also looked at whether the predictive power of net individual trading was different before and after the change in tick size (i.e., decimalization) that took place in January 2001. The smaller tick size could have reduced the profit potential of individuals from liquidity provision (e.g., due to more frequent undercutting by NYSE specialists), resulting in lower subsequent abnormal returns. We found that abnormal returns were indeed slightly higher when the tick size was larger: $CAR_{[0,61]}$ was 6.42% before the change and 5.12% afterwards. Unfortunately, this is not a clean test of the liquidity provision hypothesis because Reg FD (Fair Disclosure) took effect on October 23, 2000 and could have affected the potential for trading on private information after its implementation. Due to the fact that the dates of Reg FD and the change in tick size are so close, we cannot separate their impacts, and therefore the slight reduction in the abnormal returns could potentially be due to less information trading as well as to less profitable liquidity provision.

In order to decompose the abnormal returns into a liquidity provision component and an information component, we need to impose some structure on the return generating process. We provide several versions of this structure to examine the robustness of our assumptions. The most important aspect of our decomposition methodology is that it allows the amount of liquidity demanded to change around earnings announcements (individuals and institutions may decide to rebalance portfolios around corporate events irrespective of the information content of the event). The first version of the methodology assumes that the "market price" of liquidity provision is the same for all stocks but can change over time. The second and third versions relax this assumption and provide a more general form that allows the compensation for liquidity provision of stocks that have earnings announcements to change with risk changes around the event.

The specifics of the first version are as follows. For each day (say day *t*) during the sample period we take all the stocks in our sample that did not have earnings announcements in a 20-day window around that day, and we estimate the following two cross-sectional models:

$$\text{Model 1: } \text{CAR}^{i}_{[t,t+61]} = a_t + b_t * \text{IndNT}^{i}_{[t-10,t-1]} + c_t * \text{CAR}^{i}_{[t-10,t-1]} + \text{error}$$

$$\text{Model 2: } \text{CAR}^{i}_{[t,t+61]} = a_t + b_t * \text{IndNT}^{i}_{[t-60,t-1]} + c_t * \text{CAR}^{i}_{[t-60,t-1]} + \text{error}$$

The reason we use two models is simply for robustness, and these two models follow the time conventions we have used for the models presented in Table 5. The models give us estimated parameters that describe the relation between net individual trading and future returns (i.e., the return reversal due to risk-averse liquidity provision by individual investors) for days when individuals are less likely to have significant information.

We then use the parameter estimates from these regressions to compute the expected abnormal return due to liquidity provision for each event in the sample. Say we want to compute the expected abnormal return from liquidity provision for an earnings announcement on April 3rd, 2001 using Model 1. We take the parameter estimates of $a_{4/3/01}$, $b_{4/3/01}$, and $c_{4/3/01}$ from Model 1 above and, together with the actual values of net individual trading and return before that specific earnings announcement

($IndNT^{i}_{[3/20/01,4/2/01]}$ and $CAR^{i}_{[3/20/01,4/2/01]}$), we compute the expected abnormal return as follows:

$$\text{ECAR1}^{i}_{[4/3/01,6/27/01]} = \hat{a}_{4/3/01} + \hat{b}_{4/3/01} * \text{IndNT}^{i}_{[3/20/01,4/2/01]} + \hat{c}_{4/3/01} * \text{CAR}^{i}_{[3/20/01,4/2/01]}$$

We follow this process for each earnings announcement in our sample, in a sense estimating a "market price" of liquidity provision on the same date as the announcement and then multiplying the "market price" of liquidity by the actual imbalance before the announcement in order to compute an estimate of the compensation required for liquidity provision for that specific event. For each event we also compute $CAR_{[0,61]} – ECAR1_{[0,61]}$ as the abnormal return component that cannot be attributed to liquidity provision and hence is attributed to private information or skill.

Our procedure assumes that on non-event days, the return predictability of individual investor trades is due entirely to liquidity provision, and the effect of information trading before earnings announcements is identified as the abnormal return that cannot be explained based on the structure we impose on liquidity provision. Specifically, we subtract an estimate of the compensation individuals get for accommodating the demand for immediacy of other traders around the event and attribute the difference to the abnormal returns associated with information.

While the first version of our methodology assumes that the market price of liquidity provision is the same for all stocks on each date, inventory models in market microstructure (e.g., Stoll (1978), Ho and Stoll (1981)) and the risk-averse liquidity provision paradigm in general (e.g., Grossman and Miller (1988)) stress that the volatility (or risk) of a stock affects the price of liquidity provision. As a result, the market price of liquidity will be higher around earnings announcements if stocks are more volatile around these periods.

To account for changing levels of volatility, the second version of our decomposition methodology incorporates adjustments for volatility/risk directly into the estimation of the expected abnormal return attributed to liquidity provision. More specifically, we estimate the following two cross-sectional models each day during the sample period using all stocks that did not have earnings announcements in a 20-day window around that day:

$$\text{Model 1: } \text{CAR}^{i}_{[t,t+61]} = a_t + b_t * \text{IndNT}^{i}_{[t-10,t-1]} + c_t * \text{CAR}^{i}_{[t-10,t-1]} + d_t * \text{Risk}_{i,t} + \text{error}$$

$$\text{Model 2: } \text{CAR}^{i}_{[t,t+61]} = a_t + b_t * \text{IndNT}^{i}_{[t-60,t-1]} + c_t * \text{CAR}^{i}_{[t-60,t-1]} + d_t * \text{Risk}_{i,t} + \text{error}$$

where the difference from our initial approach is that we incorporate a risk measure for each stock, and therefore estimate a risk premium parameter that allows risk to affect future returns. We use several volatility/risk measures for robustness: (i) the standard deviation of daily returns in [-60,-1], (ii) the beta of the stock in [-60,-1] estimated using the equal-weighted portfolio of all stocks as a proxy for the market, and (iii) the standard deviation of daily returns in [-10,-1].[20]

To compute the expected abnormal return due to risk-averse liquidity provision for an event, we now take not just pre-event net individual trading and return, but also the specific risk measure (e.g., volatility in the past ten days) of that stock during the pre-event period. We then multiply these variables by the parameter estimates for the date of the announcement (including the risk premium estimate d_t) to compute the expected abnormal return. This has two advantages: first, our methodology incorporates the fact that each stock in the cross section could have a different risk measure, and second, it adjusts for the actual volatility a stock experiences in the pre-event period. If volatility increases around a certain announcement, the expected abnormal return due to liquidity provision for this announcement will be higher because the computation of ECAR1 and ECAR2 takes the actual higher volatility measure and multiplies it by the risk premium. Hence, if changes in volatility/risk that were misclassified in the first version of this methodology were driving the significant showing of an information effect, the results of the second version should exhibit a much larger liquidity component and a correspondingly smaller information component.

[20] We also conducted the analysis with volatility/risk measures computed from returns around the event rather than only before the event. More specifically, we used the standard deviation of daily returns in [-60,+60] and [-10,+10] as well as beta in [-60,+60]. The results were very similar to those using the measures computed from returns prior to the event.

The third version of our methodology allows for the possibility that volatility/risk affects the compensation for liquidity provision through both a fixed component and a variable component that depends on the amount of liquidity demanded from the individuals. To incorporate the latter component we add the interaction of the risk measure and net individual trading to the cross-sectional regressions that are estimated every day using stocks without earnings announcements in the 20-day window:

$$\text{Model 1: } \text{CAR}^i_{[t,t+61]} = a_t + b_t * \text{IndNT}^i_{[t-10,t-1]} + c_t * \text{CAR}^i_{[t-10,t-1]} + d_t * \text{Risk}_{i,t} + e_t * \text{IndNT}^i_{[t-10,t-1]} * \text{Risk}_{i,t} + \text{error}$$

$$\text{Model 2: } \text{CAR}^i_{[t,t+61]} = a_t + b_t * \text{IndNT}^i_{[t-60,t-1]} + c_t * \text{CAR}^i_{[t-60,t-1]} + d_t * \text{Risk}_{i,t} + e_t * \text{IndNT}^i_{[t-60,t-1]} * \text{Risk}_{i,t} + \text{error}$$

When we compute ECAR1 and ECAR2 for each event, we use the actual values of volatility/risk and net individual trading from the event itself, and hence the expected abnormal returns are adjusted for a potential change in volatility that interacts with the amount of liquidity demanded from individuals.

III.C. Decomposition of the Abnormal Return: Results

The results of the first version of our decomposition methodology are presented in Panel A of Table 6. Each quarter we sort all earnings announcements according to net individual trading before the event and put them in five quintiles in the same way we constructed Table 3. The first column of Panel A of Table 6 shows $\text{CAR}_{[0,61]}$ and hence is identical to the last column of Table 3. The next two columns show the component attributed to risk-averse liquidity provision (ECAR1 from Model 1 that uses a 10-day pre-event period and ECAR2 from Model 2 that uses a 60-day pre-event period) and the last two columns show the component attributed to information or skill for the two models. As in Table 3, we use the Fuller-Battese methodology (with quarterly clustering) to compute clustering-corrected t-statistics in each cell of the table.

We observe that when individuals intensely sell before the announcement (both in quintiles 1 and 2), there is a substantial portion of the abnormal return (around 2%) that cannot be explained by risk-averse liquidity provision, leaving us with the possibility that this abnormal return reflects information about the stock. When individuals buy, the picture is somewhat less clear. In quintile 4, it seems as if a substantial portion of the abnormal return is due to information or skill. However, in quintile 5 (the most intense buying) we observe that the abnormal return is mostly due to liquidity provision in that the compensation for liquidity provision is large and statistically significant (both ECAR1 and ECAR2), but the information/skill component is not statistically significant. The last row (Difference between Q5 and Q1) suggests that about half of the predictability of abnormal returns that we documented for net individual trading is due to risk-averse liquidity provision while the other half is due to information or skill.[21]

Panel B of Table 6 shows just the last row (Difference between Q5 and Q1) when we run the models separately for small, mid-cap, and large stocks. As we mentioned in Section III.A, the magnitude of the cumulative abnormal returns is larger for small stocks than for large stocks (8.03% for small stocks; 3.03% for large stocks). Model 2 (which uses a past-trading window of 60 days) shows that the component due to information or skill is about half of the abnormal return in all size categories. Model 1 (which uses a past-trading window of 10 days) provides evidence of a significant information or skill component for small stocks but not for the larger stocks, which seems plausible since smaller stocks have much less sell-side analyst coverage.

We've also applied the methodology to a subsample of events in which the price of liquidity is less likely to change around the event. Specifically, we identify the activity of NYSE specialists (the market makers on the floor of the exchange), and we assign net specialist trading in [-10, -1] into five quintiles by comparing it to their net trading in the previous four 10-day periods.[22] If there is more specialist buying (selling) than in the previous four periods, we take this event out of the sample because more intense specialist activity is more likely to be induced by an increase in the price of liquidity

[21] As we note in footnote 7, some brokers internalize a portion of the orders coming from individual investors by trading as principal against them. Say the brokerage firm Charles Schwab somehow obtained fundamental information that allows it to forecast high returns after an earnings announcement for a certain firm. They could accommodate the sell orders coming from individuals by buying the stock while shipping the buy orders from individuals to the NYSE. We would then observe that buy orders coming from individuals are associated with higher returns after the announcement. While this explanation is possible, we think it is unlikely to drive our results. It is our understanding that the algorithms used to internalize orders are usually based on order flow and market-generated high-frequency data that allow for very rapid changes, and do not usually rely on longer term fundamental information about the firm. However, if such fundamental information is used in internalization algorithms, then the component of the abnormal return that we attribute to the individuals' information or skill would be overstated.

[22] The official term for NYSE specialists has changed to Designated Market Makers in October of 2008 to correspond with certain changes in their privileges and obligations.

provision. The events that are left in this subsample, therefore, are less likely to experience a major change in the price of liquidity provision.[23] Panel C of Table 6 contains the results using this subsample, and we observe that they are very similar to the results using the full sample, suggesting that perhaps events associated with a change in the price of liquidity provision are not driving the significant showing of a private information component.

The second and third versions of the decomposition methodology allow the price of liquidity to change around earnings announcements by incorporating adjustments for volatility/risk directly into the estimation of the expected abnormal return attributed to liquidity provision. Panels A, B, and C of Table 7 report the results of the second version for the three volatility/risk measures ($Std_{[-60,-1]}$, $Beta_{[-60,-1]}$, and $Std_{[-10,-1]}$). To demonstrate the robustness of our results to the inclusion of the risk measures, we report the results for each risk measure using the entire sample as well as separately for small, mid-cap, and large stocks. To economize on the size of the table, we only report the last line "Difference between Q5 and Q1" that demonstrates the overall size of the liquidity and information components out of the total return to the zero investment strategy. The results are similar in magnitude and statistical significance to the results reported in Panel A of Table 6. If at all, the magnitude of the information component is a bit larger once we control for changes in risk around the events.

The results of the third version of our methodology that includes both the risk measure and the interaction between the risk measure and net individual trading are presented in Panel D of Table 7. We observe similar magnitudes to those without risk adjustment for both the component attributed to liquidity provision and the component attributed to private information or skill.[24] The bottom line is that we reach the same conclusion—that about half of the abnormal return could be due to information—even

[23] We also looked at another version of this test by taking out events with intense specialist activity only if specialists trade in the same direction as individuals. More specifically, we took out an event with intense specialist selling only if the event was in quintiles 1, 2, or 3 of the individuals, and similarly an event with intense specialist buying only if it was in quintiles 5, 4, or 3 of the individuals. The results were also very similar to those in Panel A of Table 6.

[24] We also obtain similar results when the second and third versions of our methodology are applied to the subsample of events used in Panel C of Table 6.

when we use a more general model that allows for changes around earnings announcements both in the amount of liquidity demanded and in the price of liquidity provision.

III.D. Dividend Announcements[25]

We focus this paper on trading around earnings announcements because the sole purpose of these corporate events is to release information to the market. Therefore, they provide an ideal environment to investigate the potential for information trading by individual investors. To examine the robustness of our analysis we examine individual trades around dividend announcements, which are also regularly scheduled events like earnings announcements.

We use the CRSP database to identify all cash dividend announcements in our sample period and subject them to the same screen as the earnings announcements: we require at least 60 days of individual trading data before the announcement. The resulting sample contains 9,251 dividend announcements in NYSE stocks from the beginning of 2000 through the end of 2003.[26] We then proceed to investigate this sample by applying the same tests we used on the earnings announcements. Specifically, we first sort all dividend announcements into quintiles based on net individual trading in the 10 days before the event and look at abnormal returns on and after the event in an analogous fashion to Table 3.[27]

Panel A of Table 8 shows that net individual trading does have predictive power with respect to abnormal returns on and after dividend announcements, but the magnitude of the effect is smaller than that around earnings announcements. Stocks that individuals intensely bought in the two weeks before the announcements outperform those that they intensely sold, on average, by 3.80% in the three months following the event ([0,61]),

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[25] We thank the referee for suggesting this analysis.

[26] We want to focus on regular dividend announcements (which are the most equivalent to regular earnings announcements) and therefore we apply the following screens: (i) we require that the dividend change from the previous quarter is no greater than 500% in order to remove outliers and eliminate the few observations of dividend initiations, and (ii) we eliminate a quarterly dividend if another type of distribution was made over the period since the previous quarterly dividend.

[27] The only difference from the procedure used to construct Table 3 for earnings announcements is that we sort annually rather than quarterly due to the smaller number of dividend announcement events (though sorting quarterly does not materially affect the results).

which is smaller than the 5.45% we report for earnings announcements. In addition, the performance of this strategy during the event window ([0,1]) is just 0.29% compared with 1.47% for earnings announcements.

We then investigate whether individual investors trade on information by decomposing these returns into liquidity and information components. We implement our decomposition methodology in exactly the same way as we do for earnings announcements in Table 6 and Table 7. We report only the "Difference between Q5 and Q1" for each version of our methodology in order to be able to show in one panel the results with and without the adjustment for volatility/risk.

Panel B of Table 8 shows that we observe a significant information component (with magnitude of about half of the abnormal returns) when we consider Model 2 that uses net individual trading 60 days prior to the event. The showing of an information component for Model 1 (which uses net individual trading 10 days before the event) is less consistent. In fact, without risk adjustment (or using beta to adjust for risk) the information component is not significantly different from zero. However, when we allow the price of liquidity to change with the volatility of the stock before the event as measured by the standard deviation of daily returns either 60 or 10 days before the event, the procedure picks up a significant information component with magnitude of about a third of the abnormal returns.

While our focus in this paper is on a direct information release event (earnings announcements), it is nonetheless interesting to find a somewhat similar pattern when we look at another event that is likely to be associated with some information. This evidence strengthens our belief in the robustness of our conclusions on the possibility of informed trading by individuals.

IV. Investor Trading after the Event

While the main research question we address in this paper concerns the potential for information trading by individuals prior to earnings announcements, in this section we look at their trading after the event. This analysis is particularly interesting because if individuals trade on information prior to the announcements, it could be that they reverse their positions after the announcements. Unfortunately, our data do not permit us to observe the strategy of specific individuals and hence we cannot unequivocally identify such trading patterns. But if such profit-taking means trading in the opposite direction to the news after the announcement, then we could potentially observe it in the aggregate, and the individuals' trading would then have the potential to impede the adjustment of prices to information. Such behavior, therefore, could potentially create or sustain the "drift," which is the empirical phenomenon that stocks with negative earnings surprises experience negative abnormal returns in the post-event period and stocks with positive earnings surprises experience positive abnormal returns in the post-event period.

Some authors have conjectured that the behavior of individuals is responsible for the slow adjustment of prices to information in earnings announcements, which manifests itself as the drift. Indirect evidence for this effect is found in Bartov, Krinsky, and Radhakrishnan (2000), who document that the drift is negatively related to the extent of institutional holdings. So far, however, there has been no direct evidence using trading data on individuals in the U.S. that is consistent with this idea. In particular, Hirshleifer, Myers, Myers, and Teoh (2008) hypothesize that if the drift reflects market misvaluation, then more sophisticated investors (i.e., institutions) should buy immediately after good news (before an upward drift) and vice versa after bad news. They conjecture that naive individual investors would take the opposite side of these transactions, and their trading would slow down the adjustment of prices to the information. Hirshleifer et al. investigate this idea using a sample of retail clients of one discount broker, but conclude that their data do not support it.

We begin our investigation of this issue by sorting all stocks each quarter according to the analysts' earnings surprise measure and putting them in five quintiles. For the presentation in Figure 1, however, we focus on quintile 1 (the most negative surprise) and quintile 5 (the most positive surprise). The figure plots net individual trading in the extreme news quintiles for several periods on and after the event. We observe a "news-contrarian" pattern: individuals buy the stocks that experience bad news (quintile 1) and sell the stocks that experience good news (quintile 5).[28] We also plot the net trading of institutional investors that is computed using information from the NYSE's CAUD files in a manner analogous to the computation of our net individual trading measure. Institutions seem to behave in a "news-momentum" manner: they sell after bad news and buy following good news.

The patterns in Figure 1 are consistent with the idea that individuals trade after earnings announcements in the direction that would slow down the adjustment of prices to the news. However, Kaniel, Saar, and Titman (2008) show that individual investors generally trade in a contrarian fashion. If prices move prior to the earnings announcements to reflect information that would only later be announced publicly, it is possible that the patterns in Figure 1 simply show the tendency of individuals to trade in response to price patterns prior to the event as opposed to trading in response to the public release of news. To distinguish between these two potential effects, we look at net trading by individuals during the event window and in the 60-day period following the event conditional on two variables: the earnings surprise and the abnormal return prior to the earnings announcement.

We sort all events according to the earnings surprise and put them in five groups: quintile 1 is the most negative surprise and quintile 5 is the most positive surprise. We also independently sort on cumulative abnormal return in the three months prior to the event.[29] Panel A of Table 9 shows a very clear picture: individuals trade during the event window predominantly in response to prior price patterns, not the earnings surprise. $IndNT_{[0,1]}$ is positive and significant (i.e., individuals buy) across the first line of the panel that corresponds to the quintile of stocks that experienced the most negative return before the event, but there is no statistically significant difference between individual

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[28] The differences in the trading of individuals between quintile 5 and quintile 1 are statistically significant in all periods (during and following the event). The statistical analysis is done using the Fuller-Battese methodology that provides clustering-corrected t-statistics.

[29] The period over which we consider return prior to the event is somewhat arbitrary, but we present the analysis using three months of return before the event because we are measuring trading over a three-month period after the event. We repeated the analysis conditioning on 20-day and 10-day returns prior to the events, and our conclusions did not change: the same (statistically significant) patterns were found conditioning on these two shorter periods.

investors buying of bad news and good news stocks. Similarly, individuals intensely sell stocks that had either positive or negative surprises if the return before the event was positive (i.e., abnormal return quintile 5).

Panel B of Table 9 looks at the trading of individuals in the 60-day period after the end of the event window, $IndNT_{[2,61]}$. Here we observe a more complex behavior. It is still the case that individuals behave as contrarians: they sell (buy) stocks that went up (down) in price before the event. However, there is also a “news-contrarian” effect whereby individuals buy more of the stocks that went down in price and had bad news than stocks that went down in price but had good news. Similarly, for stocks that had the highest return before the event, individuals seem to sell less of those stocks with bad news than those with good news.

It is interesting to note that individuals are much more active in the cells (Q1,Q1) and (Q5,Q5) of the table: the “dogs” and “angels” cells. The dogs had both the most negative return before the event and bad news, and individuals buy them almost twice as much as they buy stocks in other cells of the table. The angels had both the most positive return before the event and good news, in which case individuals sell them almost twice as much as they sell the stocks in any other cell in the table. Intense individual buying or selling therefore seems to be shaped by both past return and news in a “contrarian” fashion.

Figure 2 shows the difference in investor trading following bad news (dark bars) and good news (light bars) for both individuals and institutions, focusing on the extreme quintiles in terms of past return (CAR1 and CAR5). The figure graphically demonstrates the news-contrarian behavior of individuals, and shows that institutions exhibit “news-momentum” behavior: they buy (sell) much more of the stocks that both went up (down) in price prior to the event and had good (bad) news than those that went up (down) in price and had bad (good) news. The behavior of institutions in the post-event period therefore seems to mirror that of the individuals.

Table 10 provides another robustness test for the news-contrarian effect: we regress net individual trading in the post-event period ([2,61]) on (i) return prior to the event, (ii) net individual trading prior to the event, and (iii) two measures of earnings surprise. The first measure of earnings surprise is the analysts' earnings surprise (ES) dummies as in Table 5, and the second measure is the abnormal return at the time of the event (days [0,1]). We believe that a post-event trading pattern that goes in the opposite direction to return at the time of the announcement should not be simply labeled "contrarian" (i.e., a response to past price changes) because at the time of the announcement both the price adjustment and the analysts' earnings surprise measure are proxies for the same thing—the change in beliefs of market participants brought about by the announcement.

As in Table 5, we use the Fuller-Battese methodology to compute clustering-corrected t-statistics, and present models where pre-event abnormal returns and net individual trading are measured over either 10 days or 60 days before the announcement. The results in Table 10 demonstrate the robustness of the news-contrarian effect. The coefficients on ES1 (bad news) are positive and on ES5 (good news) are negative (and all are significant) in the first two models. Similarly, the coefficient on $CAR_{[0,1]}$ is negative and significant when it is used as the surprise measure in models 3 and 4. When we have both the ES dummies and $CAR_{[0,1]}$ in models 5 and 6, most of the coefficients that were statistically significant in the other models remain significant, which could suggest that the two proxies do not represent exactly the same phenomenon. The contrarian pattern (i.e., the negative relation between post-event net individual trading and pre-event returns) is observed in all models.

The patterns we identify in Sections III and IV could suggest that individual investors prior to the event buy (sell) the stocks that would experience high (low) abnormal returns following the event, and then reverse their positions in the post-event period. Such a trading strategy could potentially be profitable, and at the same time it could also slow down the adjustment of prices after the event and give rise to the drift. Our net individual trading measure represents a fictitious "aggregate" or representative individual investor, and therefore we cannot say for sure that the profitable strategy above is actually pursued by certain traders.[30] It is, however, consistent with the relationships between return and trading that we observe.

V. Our Findings in the Context of the Literature

V.A. Informed Individual Investor Trading

The main finding of this paper is that a significant portion of the abnormal return we detect subsequent to pre-event individual investor trading can be attributed to trading on private information. This finding is in contrast to other papers in the literature on individual investors in the U.S. that report either a negative relation or no relation between trading by individuals and future returns (see, for example, Odean (1999), Barber and Odean (2000), Welker and Sparks (2001), and Griffin, Harris, and Topaloglu (2003)).

An exception is a paper by Coval, Hirshleifer, and Shumway (2005) that investigates trades through a discount broker and documents persistence in the performance of some individual investors, who earn 12-15 basis points per day in the week after they trade. They interpret their findings as suggesting that skillful individuals exploit market inefficiencies to earn abnormal returns, but do not investigate whether this abnormal return could also be attributed to compensation for liquidity provision.

The central difference between our investigation and the few papers (mostly from outside the U.S.) documenting that some individual investor generate positive returns is our attempt to separate the compensation for liquidity provision, which does not require any special skill except "being there", from skillful trading by individuals. Linnainmaa (2010), using a dataset of individual investors from Finland, finds that individuals' market orders earn positive returns up to a three-month holding period, concluding that they may be trading on useful information. Individuals' executed limit orders, however, incur losses and therefore the three-month holding-period return on all trades by

[30] While we cannot verify the strategies of specific traders, we have observed the following pattern that is consistent with "profit-taking" behavior. Stocks that experience the greatest drift in the post-event period (i.e., both a positive earnings surprise and a positive abnormal return) show a pattern of individual investor buying prior to the announcement and selling after the announcement.

individuals is indistinguishable from zero. Che, Norli, and Priestley (2009) look at the investment performance of all individuals who own stocks that are traded on the Oslo Stock Exchange. They find performance persistence in that individuals who have done well over the past two to five years outperform a passive benchmark for as long as the next three years. In Australia, Jackson (2003) documents that net trades of clients of full-service brokers predict short-horizon returns (over the next two to three weeks), while Fong, Gallagher, and Lee (2008) find that net trades of clients of full-service retail brokers earn positive returns for up to a year (but the result is reversed for clients of discount brokers).

Focusing on trading around earnings announcements, Vieru, Perttunen, and Schadewitz (2006) investigate the trading of individual investors on the Helsinki Stock Exchange. They document that net trading by the very active individual traders in the three days prior to the event is positively related to abnormal returns in the five days that start on the event day. This, however, does not hold for all other individuals. Their result on the trading of individuals in Finland could be consistent with our findings in the U.S. in the sense that while we observe net individual trading in the aggregate (without the ability to separate different classes of individual investors), it is possible that the intense net imbalances in our dataset are driven by more active individual traders. Whether or not individuals in Finland possess useful private information is unclear because no attempt is made to account for the compensation for liquidity provision.

V.B. Our Results and the TORQ Dataset

It is interesting to note that prior work on the aggregate buying and selling of individuals around earnings announcements in the U.S. did not reveal predictive power with respect to return. More specifically, Welker and Sparks (2001) use the TORQ dataset to look at the behavior of individuals around firm-specific news articles from November 1990 through January 1991. They use intraday data to define good and bad news according to the price reaction during an interval of one and a half hours that contains the release of the news. They do not find a consistent relation between good or bad news defined in this way and the direction of trading by investors in the five days before the news release.[31]

The TORQ dataset contains data from the NYSE's CAUD files that is similar to the data we use here except that (i) we only have daily aggregated data while TORQ contains the intraday records of orders, and (ii) TORQ is a substantially smaller dataset in scope: only 144 securities for a three-month period. Why do we reach a different conclusion on the predictive ability of net individual trading? First, we look at a very different horizon: our shortest interval is two days ([0,1]) and we focus on the abnormal return in the three months after the event ([0,61]). Welker and Sparks, on the other hand, look only at the very immediate price reaction (within one and a half hours). It is possible that individual trading would have no predictive power for the price reaction in the hour after the announcement, but show strong predictive power with respect to abnormal returns of longer horizon. Second, TORQ contains very few observations of earnings announcements: Welker and Sparks use 124 news articles of which 29 involve earnings announcements. Therefore, it could simply be a power issue: they may not have enough observations to detect the pattern we observe.

To gain a better understanding of the differences between TORQ and our 2000-2003 dataset, we carry out additional empirical tests. We first use data from the TORQ dataset and attempt to replicate the results we have in our paper. The question we are trying to answer with this test is whether we would have found the same results had we used our methodology with the smaller/older dataset. We then use our own data (2000-2003) but instead of analyzing all earnings announcements, we use a smaller number of events (the same number as we can identify in TORQ) to see whether we could have found our results even in the 2000-2003 data had we analyzed only such a small number of observations.

We are able to identify 46 earnings announcements in the TORQ dataset on which we can carry out the test of Table 3: sorting into groups according to net individual

[31] While our focus is on the directional trading (buying and selling) of individuals around earnings announcements, there are papers that look at volume (i.e., non-directional trading) of different investors around these events. See, for example, Bhattacharya (2001) and Dey and Radhakrishna (2007).

trading in the 10 days prior to the event and then looking at event and post-event abnormal returns. [32] We find no statistically significant abnormal returns during the event itself ([0,1]) or over the entire period ([0,61]).[33] We also run a regression similar to the one we ran for Table 5 in the paper (predicting $CAR_{[0,61]}$ using earnings surprise dummies, pre-event net individual trading, and pre-event return). We find that the coefficient on pre-event net individual trading is positive but not statistically significant, which is consistent with having too few observations for a significant result given the level of noise in the data.

We further investigate if power is an important issue by asking whether we would have found an effect during our sample period had we used only 46 earnings announcement (as in TORQ). We generate 100 random samples of 46 events from our 2000-2003 dataset, and perform on each sample the analysis of Table 3. We find that while the abnormal returns on average have the correct signs and magnitudes, the t-statistic for the "average" 46-stock sample is very small, and most of the samples exhibit results insignificantly different from zero. Even in the most extreme buying and selling quintiles, only between 3 and 12 samples (out of 100) exhibit statistically significant abnormal returns in the right direction. These results suggest that the lack of findings in the earlier TORQ sample could simply have been due to a power issue. The relationship is somewhat noisy, and one needs more observations to find it.

[32] The TORQ dataset includes securities other than common domestic stocks (which are the securities we analyze in our study). After screening the TORQ dataset for these stocks (using CRSP share codes 10 and 11) we are left with 106 stocks (down from 144 securities). We then merge this sample with IBES and COMPUSTAT to get the earnings announcement dates, the analysts' forecasts, and the actual earnings information in order to be able to replicate the analysis we have in our paper. This procedure leaves us with only 52 stocks. The reason we lose 54 stocks is that 28 stocks report earnings in October of 1990 or early February of 1991 (the data in TORQ only covers November 1990 through January 1991), and 26 stocks do not have any information in COMPUSTAT/IBES about an earnings announcement during that period. Our analysis requires that we condition on net individual trading at least 10 days prior to the earnings announcement. This requirement eliminates 6 stocks (where the earnings announcement happens at the beginning of November). We are left with 46 earnings announcement events on which to carry out the analysis.

[33] There are statistically significant findings in [2,6] and [2,11], but it seems as if these are driven by a few dominant observations. Hence, at best this analysis suggests that the results could have been there even at the end of 1990, but with such a small sample we don't have enough observations for a statistical analysis that generates significant results.

V.C. Trading after Earnings Announcements

Our results in Section IV examine how individuals trade after earnings announcements: we show that individuals trade in a news-contrarian fashion, and hence their trading could be related to the drift phenomenon. Hirshleifer, Myers, Myres, and Teoh (2008) use a sample of clients of one discount broker from 1991 through 1996 to test the hypothesis that naive individual investors would trade in the opposite direction to the news following earnings announcements, and that their trading would slow down the adjustment of prices to the information. They find that individual investors are net buyers after negative earnings surprises, but this is not mirrored by individual selling after positive earnings surprises. Hirshleifer et al. end up concluding that their evidence does not support the hypothesis that individual investors drive the post-earnings announcement drift.[34] Lee (1992) and Shanthikumar (2004) find positive small trade imbalances, which they attribute to individual investors, after both good and bad surprises, and hence their results could not explain the drift either.[35]

The aforementioned Welker and Sparks (2001) paper also looks at net individual trading in the five days after events defined as good or bad news using their one and a half hours price reaction measure, and find that individuals react in a direction counter to the immediate price reaction. Since they do not control for past return, it is difficult to say whether this is a contrarian behavior (i.e., a response to pre-event price movement) or a news-contrarian behavior. Nonetheless, the overall contrarian pattern they find is similar in spirit to the results we document using a different definition of what constitutes an earnings surprise and a very different horizon.[36] Our results on the behavior of

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[34] Battalio and Mendenhall (2005) reach the conclusion that individual investors contribute to the drift using a different exercise. They find that large trade imbalances are correlated with analysts' forecasts errors, while small trade imbalances are correlated with forecast errors from a naive time-series model. They claim that their results are consistent with the idea that individuals display behavior that causes the post-earnings announcement drift because small trade imbalances reflect beliefs that significantly underestimate the implications of current earnings innovations for future earnings levels.

[35] Shanthikumar (2004) also finds that while large trade imbalances are indeed in the direction of the surprise in the first month after the announcement, starting from the second month small trade imbalances can be found in the direction of the surprise.

[36] Nofsinger (2001) uses TORQ to investigate individual trading in a three-day window around news articles about a variety of firm-specific and macro-economic issues. He defines good or bad news according to price reaction in the three days surrounding the event, and finds contemporaneous abnormal

individuals in the post-event period in the U.S. are also consistent with findings from Finland where Vieru, Perttunen, and Schadewitz (2005) document that individuals (especially those trading infrequently) exhibit news-contrarian behavior while institutions exhibit news-momentum behavior.[37]

VI. Conclusions

This paper documents evidence consistent with informed or skillful trading by individual investors. We show that intense aggregate individual investor buying (selling) predicts large positive (negative) abnormal returns on and after earnings announcement dates. Since the source of these abnormal returns could arise because of information held by individuals or because of the liquidity provision role of individuals, we develop a methodology that allows us to gauge the relative importance of each component. Our decomposition suggests that both components are approximately equal in importance around earnings announcements.

It is noteworthy that this is the first paper that identifies evidence of informed individual investor trading around corporate events using U.S. data. This is at least partly due to the sources of data used in prior work: the TORQ dataset is very small and hence does not provide sufficient power to detect abnormal returns, and data from a single discount broker that was used in a number of studies could be dominated by smaller and less sophisticated investors.[38] There is, however, evidence from outside the U.S.,

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individual buying in good firm-specific news events (most of which are not earnings announcements). Our focus is on post-event net individual trading (days [2,61]) rather than their contemporaneous trading, and therefore our findings do not necessarily contradict his results. Nonetheless, Panel A of Table 9 shows that net individual trading in days [0,1] during our sample period is more determined by past 60-day return than by the earnings surprise. Nofsinger does not control for past return in his analysis, and hence we cannot rule out that the results he report could be explained in part by a past-return effect. We attempted to replicate the analysis in Panel A of Table 9 (conditioning on the analysts' earnings surprise and 60-day past return) using the sample of 46 earnings announcements in TORQ. We observed that past return had a very strong influence on the results. In fact, when conditioning only on the analysts' surprise measure, net individual trading at the time of the announcement had no statistically significant direction.

[37] The result that institutions trade in a news-momentum fashion has also been documented by Welker and Sparks (2001) using TORQ and by Ke and Ramalingegowda (2005) using data on quarterly institutional holdings. Cohen, Gompers, and Vuolteenaho (2002) show that institutions buy stocks following positive cash-flow news using a measure of cash-flow news derived from a vector autoregression.

[38] However, there is significant heterogeneity among the clients of this broker, with some traders performing well in a consistent fashion (Coval, Hirshleifer, and Shumway (2005)).

discussed in Section IV, that documents profitable trading by clients of full-service brokers but finds the opposite for clients of discount brokers. Hence, it appears that the relationship between individual investor trading and future returns found in academic research critically depends on the composition of individuals in the dataset utilized for the analysis.

One interpretation of our results is that the more sophisticated individual investors that trade on the NYSE, rather than through discount brokers, are corporate insiders that are privy to special information. Another interpretation is that what we are observing is the aggregate effect of large numbers of individuals, who might serendipitously come across what turns out to be valuable information in their day-to-day activities. While information that customers, suppliers, and other individuals come across is likely to be noisy, the aggregated signal could be useful even if only a small proportion of the population obtains anything meaningful. The individuals' aggregated trading may be especially important around earnings announcements if many institutions are averse to trading too aggressively at that time for fear of litigation or adverse publicity.

To test the robustness of our results we document similar but somewhat weaker findings around dividend announcements. In addition, in unreported analysis, we looked at individual investor trading in the targets of cash acquisitions. In contrast to dividend and earnings announcements, the timing of acquisitions tends to be a surprise, which makes it less likely that institutions are seeking liquidity in anticipation of these events. On the other hand, it is possible that some individuals will be trading on private information prior to acquisition announcements, suggesting that these events may provide a cleaner test of the information hypothesis. Unfortunately, there were only a small number of such events during our sample period, and we recognize that any conclusion drawn from an analysis of such a small number of events is tentative at best. Nonetheless, we have found that the strategy that buys the stocks that individuals bought and sells the stocks they sold prior to acquisition announcements generates quite strong abnormal returns, over 80% of which are attributed by our decomposition procedure to information/skill. This evidence suggests that future work that examines trading patterns prior to a broader sample of unanticipated events is likely to be of interest.

Our evidence of individual trading behavior after the earnings announcement is also of interest. Specifically, we show that individuals exhibit what we call news-contrarian behavior, e.g., selling after good earnings announcements, as well as the return contrarian behavior described in earlier studies. An earlier study by Hirshleifer et al. (2008) conjectured that this type of behavior might be irrational, leading individuals to lose money because of the post-earnings announcement drift. However, an alternative explanation, consistent with our evidence of positive abnormal returns when individuals buy prior to earnings announcements, is that individuals sell after good earnings announcements because they are profitably reversing positions they entered into prior to the announcements.

While our comprehensive dataset enables us to investigate the sources of the predictive power in individual investor trading and to document interesting patterns following the events, it nonetheless has some limitations. Most notably, we do not observe the strategies of specific individuals, and hence are unable to definitively answer the question whether trading by individuals after the event is naive or rather it is part of a profit-taking strategy. It is likely that there is some heterogeneity among individual investors, and hence more fine-tuned conclusions would require better data.

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Table 1
Summary Statistics

The sample of stocks for the study consists of all common, domestic stocks that were traded on the NYSE at any time between January 1, 2000 and December 31, 2003 with records in the CRSP database. We use ticker symbol and CUSIP to match the stocks to a special dataset containing daily aggregated buying and selling volume of individuals that was provided to us by the NYSE. We then use IBES and COMPUSTAT to identify all the dates where stocks in our sample had earnings announcements, and impose two restrictions on the sample. First, we require 60 days of data prior to and after the announcements. Second, we require that there is an observation in the IBES database of mean analysts' forecast in the month prior to the earnings announcement (and also the actual earnings number). Our screens result in a final sample of 1,821 stocks with 17,564 earnings announcement events. In Panel A, we provide summary statistics from the CRSP database. For each stock we compute the following time-series measures: AvgCap is the average monthly market capitalization over the sample period; AvgPrc is the average daily closing price; AvgTurn is the average weekly turnover (number of shares traded divided by the number of shares outstanding); AvgVol is the average weekly dollar volume; and StdRet is the standard deviation of weekly returns. We then sort the stocks by market capitalization into ten deciles, and form three size groups: small stocks (deciles 1, 2, 3, and 4), mid-cap stocks (deciles 5, 6, and 7), and large stocks (deciles 8, 9, and 10). The cross-sectional mean and median of these measures are presented for the entire sample and separately for the three size groups. In Panel B, we provide the number of earnings announcement events used in the analysis for each month during the sample period.

Panel A: Summary Statistics of Sample Stocks (from CRSP)

		AvgCap (in million $)	**AvgPrc** (in $)	**AvgTurn** (in %)	**AvgVol** (in million $)	**StdRet** (in %)
All stocks	Mean	5,783.5	64.16	2.67	125.00	7.26
	Median	1,049.8	22.87	2.19	27.06	6.11
Small stocks	Mean	354.5	15.49	2.65	11.34	8.84
	Median	353.2	12.40	1.83	5.86	7.36
Mid-Cap stocks	Mean	1,367.5	27.28	3.29	45.74	6.76
	Median	1,279.6	24.37	2.62	34.15	6.01
Large stocks	Mean	14,652.0	140.38	3.25	321.40	6.07
	Median	5,314.5	37.59	2.61	170.62	5.32

Panel B: Number of Earnings Announcement Events in our Sample

	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
2000	0	0	17	949	343	84	929	345	90	786	288	86
2001	638	488	160	852	283	82	829	338	71	866	289	78
2002	626	456	120	843	304	73	879	282	78	903	272	87
2003	589	510	148	851	318	75	879	290	80	10	0	0
All years	1853	1454	445	3495	1248	314	3516	1255	319	2565	849	251

Table 2

Net Individual Trading around Earnings Announcements

This table presents net individual trading around earnings announcements. We construct the net individual trading measure by first computing an imbalance measure: subtracting the daily value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year. We then subtract from the imbalance measure the daily average of individual imbalances over the sample period to get the net individual trading measure, and compute for each stock the cumulative net individual trading measure over certain periods before, during, and after the announcement. Since each week contains multiple earnings announcements, we implement the Fuller-Battese methodology to correct for clustering. For each quintile, we model the net individual trading measure using a one-way random effect framework in which there is a weekly effect (for [-5,-1,], [0,1], and [2,6]), a monthly effect (for [-20,-1], [-10,-1], [2,11], and [2,21]), or a quarterly effect (for [-60,-1] and [2,61]). We report the estimated mean with clustering-corrected t-statistics (testing the hypothesis of zero net individual trading). We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

		Time Periods								
		[-60,-1]	[-20,-1]	[-10,-1]	[-5,-1]	[0,1]	[2,6]	[2,11]	[2,21]	[2,61]
All stocks	Mean	0.061	0.032	0.022*	0.017**	-0.005*	-0.015**	-0.016	-0.019	0.048
	t-stat.	(0.62)	(1.64)	(2.30)	(4.77)	(-2.15)	(-3.39)	(-1.30)	(-0.85)	(0.48)
Small Stocks	Mean	0.116	0.053	0.034	0.030**	-0.008	-0.017	-0.012	-0.005	0.057
	t-stat.	(0.70)	(1.54)	(1.88)	(4.24)	(-1.66)	(-1.84)	(-0.50)	(-0.11)	(0.36)
Mid-Cap Stocks	Mean	0.000	0.029	0.021*	0.004	-0.001	-0.018**	-0.027**	-0.039*	0.003
	t-stat.	(0.00)	(1.46)	(2.24)	(0.38)	(-0.40)	(-4.07)	(-2.71)	(-2.05)	(0.04)
Large Stocks	Mean	-0.016	0.010	0.008	0.005**	-0.003**	-0.008**	-0.009	-0.013	0.005
	t-stat.	(-0.37)	(0.98)	(1.57)	(2.62)	(-2.90)	(-4.30)	(-1.95)	(-1.43)	(0.11)

Table 3

Predicting Returns using Net Individual Trading before the Announcements

This table presents analysis of market-adjusted returns on and after earnings announcements conditional on different levels of net individual trading before the event. We construct the net individual trading measure by first computing an imbalance measure: subtracting the daily value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year. We then subtract from the imbalance measure the daily average of individual imbalances over the sample period to get the net individual trading measure, and compute for each stock the cumulative net individual trading measure in the 10 days before the announcement. In Panel A, we sort all stocks each quarter according to net individual trading in the 10 trading days prior to the announcement ($IndNT_{[-10,-1]}$), and put the stocks in five categories (quintile 1 contains the stocks that individuals sold the most and quintile 5 contains the stocks individuals bought the most). We then compute for each stock the cumulative market-adjusted return over certain periods. Since each week contains multiple earnings announcements, we implement the Fuller-Battese methodology to correct for clustering. For each quintile, we model the cumulative abnormal return using a one-way random effect framework in which there is a weekly effect (for [0,1] and [2,6]), a monthly effect (for [2,11] and [2,21]), or a quarterly effect (for [2,61] and [0,61]). We report the estimated means with clustering-corrected t-statistics (testing the hypothesis of zero cumulative abnormal return). In Panel B, we separately sort large, mid-cap, and small stocks into quintiles according to net individual trading before the event, and report just the row "Difference between Q5 and Q1" for each of these size groups. We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Panel A: Predicting Returns with Pre-Event Net Individual Trading

		Time Periods					
$IndNT_{[-10,-1]}$		[0,1]	[2,6]	[2,11]	[2,21]	[2,61]	[0,61]
Q1	Mean	-0.0066**	-0.0041**	-0.0045**	-0.0096**	-0.0281**	-0.0338**
(Selling)	t-stat.	(-4.74)	(-3.82)	(-2.99)	(-4.20)	(-5.76)	(-5.91)
Q2	Mean	0.0001	0.0005	0.0007	-0.0016	-0.0208**	-0.0198**
	t-stat.	(0.06)	(0.46)	(0.33)	(-0.59)	(-3.39)	(-3.34)
Q3	Mean	0.0037**	0.0042**	0.0056**	0.0087**	-0.0012	0.0030
	t-stat.	(2.57)	(3.37)	(2.69)	(2.76)	(-0.21)	(0.57)
Q4	Mean	0.0085**	0.0074**	0.0104**	0.0140**	0.0102**	0.0191**
	t-stat.	(6.24)	(5.89)	(4.99)	(4.82)	(2.70)	(4.80)
Q5	Mean	0.0078**	0.0031*	0.0057**	0.0096**	0.0139	0.0215**
(Buying)	t-stat.	(4.44)	(2.28)	(2.97)	(3.19)	(1.91)	(2.88)
Diff. bet.	Mean	0.0147**	0.0072**	0.0100**	0.0187**	0.0413**	0.0545**
Q5 and Q1	t-stat.	(7.48)	(4.16)	(4.31)	(6.04)	(7.80)	(9.53)

Panel B: Return Predictability by Market Capitalization Groups

			Time Periods					
	$IndNT_{[-10,-1]}$		[0,1]	[2,6]	[2,11]	[2,21]	[2,61]	[0,61]
Small	Diff. bet.	Mean	0.0216**	0.0105**	0.0198**	0.0272**	0.0598**	0.0803**
Stocks	Q5 and Q1	t-stat.	(5.46)	(2.88)	(4.13)	(4.53)	(5.63)	(7.01)
Mid-Cap	Diff. bet.	Mean	0.0152**	0.0057*	0.0053	0.0096*	0.0224**	0.0351**
Stocks	Q5 and Q1	t-stat.	(5.21)	(2.30)	(1.60)	(2.15)	(2.90)	(4.18)
Large	Diff. bet.	Mean	0.0099**	0.0074**	0.0086**	0.0111**	0.0197**	0.0303**
Stocks	Q5 and Q1	t-stat.	(3.71)	(3.76)	(3.15)	(2.99)	(2.95)	(4.15)

Table 4

Returns Following the Event: Past Return and Earnings Surprises

This table presents analysis of market-adjusted returns following earnings announcements conditional on different levels of net individual trading before the event ($IndNT_{[-10,-1]}$) and either past return (in Panel A) or the extent of earnings surprise (in Panel B). We construct the net individual trading measure by first computing an imbalance measure: subtracting the daily value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year, and then subtracting the mean daily imbalance over the sample period. In Panel A, we sort stocks into five quintiles on cumulative market-adjusted return in [-10,-1] ($CAR_{[-10,-1]}$), and within each quintile we sort on net individual trading before the event. We then compute for each stock the cumulative market-adjusted return in [0,61]. We implement the Fuller-Battese methodology to correct for clustering: for each of the 25 categories, we model the cumulative abnormal return using a one-way random effect framework in which there is a quarterly effect, and report the estimated means with clustering-corrected t-statistics (testing the hypothesis of zero cumulative abnormal return). In Panel B, we sort stocks into quintiles on the earnings surprise measure (ES), and within each quintile we sort on net individual trading before the event ($IndNT_{[10,-1]}$). Earnings surprise (ES) is defined as the actual earnings minus the earnings forecast one month before the announcement, divided by the price on the forecast day. We report for each cell the estimated mean for $CAR_{[0,61]}$ with clustering-corrected t-statistics (from the Fuller-Battese methodology with quarterly clustering). We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Panel A: Cumulative Abnormal Return in [0,61] Conditional on $CAR_{[-10,-1]}$ and $IndNT_{[-10,-1]}$

		(Negative)		**$CAR_{[-10,-1]}$**		(Positive)	Diff. bet.
$IndNT_{[-10,-1]}$		Q1	Q2	Q3	Q4	Q5	Q5 and Q1
Q1	Mean	-0.0263*	-0.0341**	-0.0311**	-0.0348**	-0.0370**	-0.0107
(Selling)	t-stat.	(-2.09)	(-4.73)	(-4.49)	(-4.78)	(-3.68)	(-0.79)
Q2	Mean	-0.0150	0.0000	-0.0195*	-0.0259**	-0.0322**	-0.0171
	t-stat.	(-1.19)	(0.00)	(-2.07)	(-2.57)	(-3.42)	(-1.40)
Q3	Mean	0.0138	0.0137	-0.0019	-0.0055	-0.0052	-0.0187
	t-stat.	(1.34)	(1.80)	(-0.18)	(-0.58)	(-0.38)	(-1.40)
Q4	Mean	0.0339**	0.0182	0.0185*	0.0064	0.0197	-0.0141
	t-stat.	(2.95)	(1.61)	(2.20)	(0.77)	(1.48)	(-0.95)
Q5	Mean	0.0295	0.0266*	0.0232**	0.0026	0.0223	-0.0077
(Buying)	t-stat.	(1.79)	(2.18)	(2.97)	(0.25)	(1.09)	(-0.45)
Diff. bet.	Mean	0.0555**	0.0611**	0.0543**	0.0371**	0.0584**	
Q5 and Q1	t-stat.	(3.37)	(5.80)	(5.21)	(3.49)	(4.12)	

Panel B: Cumulative Abnormal Return in [0,61] Conditional on ES and $IndNT_{[-10,-1]}$

		(Negative)		**ES**		(Positive)	Diff. bet.
$IndNT_{[-10,-1]}$		Q1	Q2	Q3	Q4	Q5	Q5 and Q1
Q1	Mean	-0.0746**	-0.0492**	-0.0353**	-0.0192*	0.0002	0.0758**
(Selling)	t-stat.	(-4.54)	(-5.72)	(-2.78)	(-2.46)	(0.01)	(5.77)
Q2	Mean	-0.0251	-0.0277**	-0.0213	-0.0131	0.0133	0.0387**
	t-stat.	(-1.86)	(-3.29)	(-1.74)	(-1.58)	(1.31)	(2.95)
Q3	Mean	-0.0146	-0.0194*	-0.0051	0.0188	0.0363**	0.0515**
	t-stat.	(-0.87)	(-2.30)	(-0.27)	(1.95)	(3.92)	(3.63)
Q4	Mean	0.0022	-0.0053	0.0108	0.0201*	0.0728**	0.0715**
	t-stat.	(0.14)	(-0.51)	(1.15)	(2.03)	(6.31)	(4.79)
Q5	Mean	-0.0049	0.0075	0.0077	0.0132	0.0732**	0.0786**
(Buying)	t-stat.	(-0.30)	(0.72)	(0.92)	(1.34)	(5.74)	(4.73)
Diff. bet.	Mean	0.0701**	0.0596**	0.0385**	0.0320**	0.0730**	
Q5 and Q1	t-stat.	(4.41)	(6.43)	(3.43)	(3.18)	(5.22)	

Table 5

Regressions Relating Pre-Event Trading of Individuals to Future Abnormal Returns

This table presents a regression analysis relating abnormal returns on and after the event ($CAR_{[0,61]}$) to pre-event trading by individuals. The dependent variable in the regressions is the cumulative abnormal return ($CAR_{[0,61]}$), and the regressors include dummy variables for quintiles 1, 2, 4, and 5 of the earnings surprise measure (ES), net individual trading before the event ($IndNT_{[-10,-1]}$ or $IndNT_{[-60,-1]}$), and past abnormal return. To get the ES dummies, we sort stocks into quintiles every quarter on the earnings surprise measure. Earnings surprise (ES) is defined as the actual earnings minus the earnings forecast one month before the announcement, divided by the price on the forecast day. We construct the net individual trading measure ($IndNT_{[-10,-1]}$ and $IndNT_{[-60,-1]}$) by first computing a daily imbalance measure: subtracting the value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year. We then subtract from the imbalance measure the daily average of individual imbalances over the sample period to get the net individual trading measure, and compute for each stock the cumulative net individual trading measure over these two periods before the announcement. In order to overcome potential econometric problems associated with contemporaneously correlated errors for earnings announcements that are clustered in time, we implement the Fuller-Battese methodology. This approach uses a one-way random effect model in which there is a quarterly effect, and enables us to compute clustering-corrected t-statistics for the coefficients. We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Intercept	ES1	ES2	ES4	ES5	$IndNT_{[-60,-1]}$	$IndNT_{[-10,-1]}$	$CAR_{[-60,-1]}$	$CAR_{[-10,-1]}$
-0.0051	-0.0217**	-0.0149**	0.0090	0.0444**		0.0349**		-0.0640**
(-1.00)	(-3.64)	(-2.61)	(1.51)	(7.46)		(8.39)		(-3.46)
-0.0038	-0.0214**	-0.0152**	0.0088	0.0424**	0.0107**		0.0077	
(-0.73)	(-3.57)	(-2.67)	(1.47)	(7.12)	(9.88)		(0.91)	

Table 6
Decomposition of the Abnormal Return following Individual Trading

This table presents a decomposition of market-adjusted returns following pre-event individual investor trading into a portion that is attributed to liquidity provision and a portion that is attributed to information (or skill). For each day (say day *t*) during the sample period we take all the stocks in our sample that did not have earnings announcements in a 20-day window around that day, and we estimate the following two cross-sectional models:

$$\text{Model 1: } \text{CAR}^{i}_{[t,t+61]} = a_t + b_t * \text{IndNT}^{i}_{[t-10,t-1]} + c_t * \text{CAR}^{i}_{[t-10,t-1]} + \text{error}$$

$$\text{Model 2: } \text{CAR}^{i}_{[t,t+61]} = a_t + b_t * \text{IndNT}^{i}_{[t-60,t-1]} + c_t * \text{CAR}^{i}_{[t-60,t-1]} + \text{error}$$

The models give us estimated parameters that describe the relation between net individual trading and future return for each day in the sample period. To compute the expected abnormal return due to liquidity provision for a certain earnings announcement, we take the estimated parameters for the day of the announcement from Model 1 and the actual values of net individual trading and return before the specific earnings announcement and use them to compute the expected abnormal return according to Model 1:

$$\text{ECAR1}^{i}_{[0,61]} = \hat{a}_0 + \hat{b}_0 * \text{IndNT}^{i}_{[-10,-1]} + \hat{c}_0 * \text{CAR}^{i}_{[-10,-1]}$$

A similar construction produces the estimate $\text{ECAR2}^{i}_{[0,61]}$ using the parameters estimated from Model 2. We follow this process for each earnings announcement in our sample. We also compute for each event a return component that is attributed to information/skill by taking the difference between the actual abnormal return and the estimate of the abnormal return due to liquidity provision ($\text{CAR}_{[0,61]} - \text{ECAR1}_{[0,61]}$ and $\text{CAR}_{[0,61]} - \text{ECAR2}_{[0,61]}$). In Panel A, we sort all stocks each quarter according to net individual trading in the 10 trading days prior to the announcement ($\text{IndNT}_{[-10,-1]}$), and put the stocks in five categories (quintile 1 contains the stocks that individuals sold the most and quintile 5 contains the stocks individuals bought the most). Since each quarter contains multiple earnings announcements, we implement the Fuller-Battese methodology to correct for clustering. In Panel B, we separately sort large, mid-cap, and small stocks into quintiles according to net individual trading before the event, and report just the row "Difference between Q5 and Q1" for each of these size groups. In Panel C, we take out events where the NYSE specialists' trading activity (either buying or selling) in the 10 days prior to the announcement is high relative to their activity in the same stock in the previous four 10-day periods (to eliminate events where the price of liquidity provision before the event could have changed significantly). We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Panel A: Return Decomposition into Liquidity Provision and Information Components

$\text{IndNT}_{[-10,-1]}$		$\text{CAR}_{[0,61]}$	$\text{ECAR1}_{[0,61]}$	$\text{ECAR2}_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
Q1	Mean	-0.0338**	-0.0112**	-0.0092*	-0.0223**	-0.0249**
(Selling)	t-stat.	(-5.91)	(-2.77)	(-2.22)	(-4.37)	(-4.65)
Q2	Mean	-0.0198**	-0.0010	-0.0006	-0.0199*	-0.0208*
	t-stat.	(-3.34)	(-0.24)	(-0.13)	(-2.06)	(-2.10)
Q3	Mean	0.0030	0.0017	0.0016	0.0020	0.0021
	t-stat.	(0.57)	(0.44)	(0.35)	(0.22)	(0.22)
Q4	Mean	0.0191**	0.0051	0.0049	0.0138*	0.0144
	t-stat.	(4.80)	(1.29)	(0.97)	(2.14)	(1.87)
Q5	Mean	0.0215**	0.0174**	0.0145*	0.0039	0.0079
(Buying)	t-stat.	(2.88)	(3.07)	(2.47)	(0.43)	(0.84)
Diff. bet. Q5	Mean	0.0545**	0.0290**	0.0221**	0.0255**	0.0323**
and Q1	t-stat.	(9.53)	(29.68)	(20.46)	(4.44)	(5.69)

Panel B: Return Decomposition by Market Capitalization Groups

	$\text{IndNT}_{[-10,-1]}$		$\text{CAR}_{[0,61]}$	$\text{ECAR1}_{[0,61]}$	$\text{ECAR2}_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
Small	Diff. bet.	Mean	0.0803**	0.0469**	0.0354**	0.0334**	0.0448**
Stocks	Q5 and Q1	t-stat.	(7.01)	(21.44)	(14.34)	(2.90)	(3.92)
Mid-Cap	Diff. bet.	Mean	0.0351**	0.0235**	0.0120**	0.0116	0.0231**
Stocks	Q5 and Q1	t-stat.	(4.18)	(11.28)	(5.86)	(1.37)	(2.71)
Large	Diff. bet.	Mean	0.0303**	0.0300**	0.0139**	0.0003	0.0164*
Stocks	Q5 and Q1	t-stat.	(4.15)	(12.82)	(6.78)	(0.04)	(2.21)

Panel C: Return Decomposition Excluding Announcements with High Specialist Pre-Event Trading

IndNT$_{[-10,-1]}$		CAR$_{[0,61]}$	ECAR1$_{[0,61]}$	ECAR2$_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
Q1	Mean	-0.0318**	-0.0101**	-0.0094*	-0.0214**	-0.0226**
(Selling)	t-stat.	(-5.14)	(-2.58)	(-2.39)	(-3.79)	(-4.16)
Q2	Mean	-0.0178**	-0.0002	0.0002	-0.0175	-0.0180
	t-stat.	(-2.76)	(-0.06)	(0.04)	(-1.70)	(-1.70)
Q3	Mean	0.0031	0.0018	0.0021	0.0022	0.0019
	t-stat.	(0.58)	(0.44)	(0.45)	(0.25)	(0.20)
Q4	Mean	0.0213**	0.0057	0.0048	0.0156*	0.0162*
	t-stat.	(4.20)	(1.41)	(0.91)	(2.28)	(2.01)
Q5	Mean	0.0258**	0.0171**	0.0144*	0.0088	0.0123
(Buying)	t-stat.	(3.24)	(2.92)	(2.34)	(0.98)	(1.29)
Diff. bet.	Mean	0.0570**	0.0276**	0.0227**	0.0296**	0.0345**
Q5 and Q1	t-stat.	(7.83)	(23.42)	(16.91)	(4.06)	(4.77)

Table 7
Decomposition of the Abnormal Return with Risk Adjustment

This table presents the decomposition of market-adjusted returns following pre-event individual investor trading using several versions of our methodology that adjust the liquidity provision component for changes in volatility/risk around the event. For each day (say day *t*) during the sample period we take all the stocks in our sample that did not have earnings announcements in a 20-day window around that day, and we estimate the following two cross-sectional models:

$$\text{Model 1: } \text{CAR}^i_{[t,t+61]} = a_t + b_t * \text{IndNT}^i_{[t-10,t-1]} + c_t * \text{CAR}^i_{[t-10,t-1]} + d_t * \text{Risk}_{i,t} + \text{error}$$

$$\text{Model 2: } \text{CAR}^i_{[t,t+61]} = a_t + b_t * \text{IndNT}^i_{[t-60,t-1]} + c_t * \text{CAR}^i_{[t-60,t-1]} + d_t * \text{Risk}_{i,t} + \text{error}$$

The models give us estimated parameters that describe the relation between net individual trading and future return for each day in the sample period. To compute the expected abnormal return due to risk-averse liquidity provision for an event, we take not just pre-event net individual trading and return as in Table 6, but also the specific risk measure of that stock during the pre-event period. We then multiply these variables by the parameter estimates for the date of the announcement (including the risk premium estimate d_t) to compute the expected abnormal return. We follow this process for each earnings announcement in our sample. We also compute for each event a return component that is attributed to information/skill by taking the difference between the actual abnormal return and the estimate of the abnormal return due to liquidity provision ($\text{CAR}_{[0,61]} - \text{ECAR1}_{[0,61]}$ and $\text{CAR}_{[0,61]} - \text{ECAR2}_{[0,61]}$). We sort all stocks each quarter according to net individual trading in the 10 trading days prior to the announcement ($\text{IndNT}_{[-10,-1]}$), and put the stocks in five categories (quintile 1 contains the stocks that individuals sold the most and quintile 5 contains the stocks individuals bought the most). We report just the row "Difference between Q5 and Q1" for the entire sample and for each of the size groups. Since each quarter contains multiple earnings announcements, we implement the Fuller-Battese methodology to correct for clustering. In Panel A, the risk measure is the standard deviation of daily return in the 60 days prior to the event ($\text{Std}_{[-60,-1]}$). In Panel B, the risk measure is the beta of the stock estimated over the 60 days prior to the event using the equal-weighted portfolio of all stocks as a proxy for the market ($\text{Beta}_{[-60,-1]}$). In Panel C, the risk measure is the standard deviation of daily return in the 10 days prior to the event ($\text{Std}_{[-10,-1]}$). In Panel D, we present the results of the decomposition using a different version of the methodology where we include both a risk term and the interaction between risk and net individual trading. Hence, the daily cross-sectional models that we estimate have the following form:

$$\text{Model 1: } \text{CAR}^i_{[t,t+61]} = a_t + b_t * \text{IndNT}^i_{[t-10,t-1]} + c_t * \text{CAR}^i_{[t-10,t-1]} + d_t * \text{Risk}_{i,t} + e_t * \text{IndNT}^i_{[t-10,t-1]} * \text{Risk}_{i,t} + \text{error}$$

$$\text{Model 2: } \text{CAR}^i_{[t,t+61]} = a_t + b_t * \text{IndNT}^i_{[t-60,t-1]} + c_t * \text{CAR}^i_{[t-60,t-1]} + d_t * \text{Risk}_{i,t} + e_t * \text{IndNT}^i_{[t-60,t-1]} * \text{Risk}_{i,t} + \text{error}$$

The rest of the steps of the procedure are similar to those in panels A, B, and C. We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Panel A: Return Decomposition with Risk Measure $\text{Std}_{[-60,-1]}$

	$\text{IndNT}_{[-10,-1]}$		$\text{CAR}_{[0,61]}$	$\text{ECAR1}_{[0,61]}$	$\text{ECAR2}_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
All	Diff. bet.	Mean	0.0545**	0.0252**	0.0187**	0.0293**	0.0358**
Stocks	Q5 and Q1	t-stat.	(9.53)	(16.16)	(11.42)	(5.24)	(6.42)
Small	Diff. bet.	Mean	0.0803**	0.0388**	0.0289**	0.0414**	0.0514**
Stocks	Q5 and Q1	t-stat.	(7.01)	(11.18)	(7.92)	(3.67)	(4.56)
Mid-Cap	Diff. bet.	Mean	0.0351**	0.0184**	0.0068*	0.0167*	0.0283**
Stocks	Q5 and Q1	t-stat.	(4.18)	(6.94)	(2.55)	(2.00)	(3.37)
Large	Diff. bet.	Mean	0.0303**	0.0256**	0.0143**	0.0047	0.0160*
Stocks	Q5 and Q1	t-stat.	(4.15)	(9.09)	(5.24)	(0.65)	(2.22)

Panel B: Return Decomposition with Risk Measure $Beta_{[-60,-1]}$

	$IndNT_{[-10,-1]}$		$CAR_{[0,61]}$	$ECAR1_{[0,61]}$	$ECAR2_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
All	Diff. bet.	Mean	0.0545**	0.0276**	0.0210**	0.0268**	0.0334**
Stocks	Q5 and Q1	t-stat.	(9.53)	(22.76)	(16.59)	(4.70)	(5.91)
Small	Diff. bet.	Mean	0.0803**	0.0476**	0.0353**	0.0327**	0.0449**
Stocks	Q5 and Q1	t-stat.	(7.01)	(17.96)	(12.79)	(2.84)	(3.93)
Mid-Cap	Diff. bet.	Mean	0.0351**	0.0151**	0.0061*	0.0200*	0.0289**
Stocks	Q5 and Q1	t-stat.	(4.18)	(5.37)	(2.19)	(2.39)	(3.44)
Large	Diff. bet.	Mean	0.0303**	0.0292**	0.0138**	0.0011	0.0165*
Stocks	Q5 and Q1	t-stat.	(4.15)	(10.65)	(5.56)	(0.14)	(2.26)

Panel C: Return Decomposition with Risk Measure $Std_{[-10,-1]}$

	$IndNT_{[-10,-1]}$		$CAR_{[0,61]}$	$ECAR1_{[0,61]}$	$ECAR2_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
All	Diff. bet.	Mean	0.0545**	0.0248**	0.0191**	0.0296**	0.0354**
Stocks	Q5 and Q1	t-stat.	(9.53)	(17.41)	(12.84)	(5.22)	(6.26)
Small	Diff. bet.	Mean	0.0803**	0.0401**	0.0320**	0.0402**	0.0483**
Stocks	Q5 and Q1	t-stat.	(7.01)	(11.10)	(8.61)	(3.45)	(4.17)
Mid-Cap	Diff. bet.	Mean	0.0351**	0.0194**	0.0074*	0.0157	0.0277**
Stocks	Q5 and Q1	t-stat.	(4.18)	(6.69)	(2.56)	(1.85)	(3.25)
Large	Diff. bet.	Mean	0.0303**	0.0265**	0.0151**	0.0038	0.0152*
Stocks	Q5 and Q1	t-stat.	(4.15)	(9.33)	(5.82)	(0.51)	(2.09)

Panel D: Return Decomposition with the Interaction of Risk and Individual Trading

Risk Measure	**$IndNT_{[-10,-1]}$**		$CAR_{[0,61]}$	$ECAR1_{[0,61]}$	$ECAR2_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
$Std_{[-60,-1]}$	Diff. bet.	Mean	0.0545**	0.0258**	0.0158**	0.0287**	0.0387**
+Interac.	Q5 and Q1	t-stat.	(9.53)	(12.28)	(9.23)	(4.92)	(6.94)
$Beta_{[-60,-1]}$	Diff. bet.	Mean	0.0545**	0.0315**	0.0204**	0.0230**	0.0341**
+Interac.	Q5 and Q1	t-stat.	(9.53)	(23.04)	(14.90)	(4.00)	(6.00)
$Std_{[-10,-1]}$	Diff. bet.	Mean	0.0545**	0.0295**	0.0172**	0.0250**	0.0372**
+Interac.	Q5 and Q1	t-stat.	(9.53)	(6.07)	(6.56)	(3.35)	(6.23)

Table 8

Analysis of Return Predictability around Dividend Announcements

This table presents analysis of market-adjusted returns on and after dividend announcements conditional on different levels of net individual trading before the event. Our sample contains 9,251 cash dividend announcements in NYSE stocks from 2000 to 2003 that we identify using the CRSP database. In Panel A, we sort all stocks each year according to net individual trading in the 10 trading days prior to the announcement ($IndNT_{[-10,-1]}$), and put the stocks in five categories (quintile 1 contains the stocks that individuals sold the most and quintile 5 contains the stocks individuals bought the most). We then compute for each stock the cumulative market-adjusted return over certain periods. Since each week contains multiple earnings announcements, we implement the Fuller-Battese methodology to correct for clustering. In Panel B, we present the decomposition of market-adjusted returns, $CAR_{[0,61]}$, into a portion that is attributed to liquidity provision and a portion that is attributed to information (or skill). The decomposition methodology is identical to that used for earnings announcements. We report the “Difference between Q5 and Q1” numbers that reflect the abnormal return to the strategy that buys the stocks that individuals bought in the 10 days before the event and sells the stocks that they sold over that period. Each line in the panel reports the return to the same strategy decomposed using a different version of our methodology (using various specifications and volatility/risk measures). These versions are equivalent to those reported for earnings announcements in Panel A of Table 6 and Panels A, B, C, and D of Table 7. We use “**” to indicate significance at the 1% level and “*” to indicate significance at the 5% level (both against a two-sided alternative).

Panel A: Predicting Returns using Net Individual Trading before Dividend Announcements

		Time Periods					
$IndNT_{[-10,-1]}$		[0,1]	[2,6]	[2,11]	[2,21]	[2,61]	[0,61]
Q1	Mean	-0.0012	-0.0031**	-0.0045**	-0.0094**	-0.0248**	-0.0259**
(Selling)	t-stat.	(-1.21)	(-2.90)	(-2.94)	(-3.57)	(-4.11)	(-4.23)
Q2	Mean	-0.0009	-0.0001	-0.0008	-0.0027	-0.0183**	-0.0195**
	t-stat.	(-1.05)	(-0.06)	(-0.48)	(-1.13)	(-4.82)	(-4.37)
Q3	Mean	0.0007	0.0011	0.0011	-0.0004	-0.0068	-0.0059
	t-stat.	(0.86)	(0.92)	(0.66)	(-0.18)	(-1.82)	(-1.59)
Q4	Mean	0.0032**	0.0022*	0.0059**	0.0060**	0.0075	0.0103*
	t-stat.	(3.57)	(2.06)	(3.59)	(2.61)	(1.70)	(2.32)
Q5	Mean	0.0016	0.0023	0.0038	0.0073**	0.0101*	0.0124*
(Buying)	t-stat.	(1.58)	(1.43)	(1.86)	(2.67)	(2.02)	(2.14)
Diff. bet.	Mean	0.0029*	0.0056**	0.0082**	0.0161**	0.0349**	0.0380**
Q5 and Q1	t-stat.	(2.13)	(2.98)	(3.39)	(4.93)	(6.51)	(6.84)

Panel B: Return Decomposition for Dividend Announcement Events

Risk Measure	**$IndNT_{[-10,-1]}$**		$CAR_{[0,61]}$	$ECAR1_{[0,61]}$	$ECAR2_{[0,61]}$	CAR-ECAR1	CAR-ECAR2
	Diff. bet.	Mean	0.0380**	0.0277**	0.0205**	0.0105	0.0178**
	Q5 and Q1	t-stat.	(6.84)	(22.62)	(14.82)	(1.89)	(3.20)
$Std_{[-60,-1]}$	Diff. bet.	Mean	0.0380**	0.0246**	0.0173**	0.0138*	0.0208**
	Q5 and Q1	t-stat.	(6.84)	(15.96)	(10.33)	(2.50)	(3.77)
$Beta_{[-60,-1]}$	Diff. bet.	Mean	0.0380**	0.0284**	0.0211**	0.0098	0.0171**
	Q5 and Q1	t-stat.	(6.84)	(19.34)	(13.35)	(1.77)	(3.09)
$Std_{[-10,-1]}$	Diff. bet.	Mean	0.0380**	0.0244**	0.0185**	0.0138*	0.0196**
	Q5 and Q1	t-stat.	(6.84)	(15.93)	(11.09)	(2.51)	(3.55)
$Std_{[-60,-1]}$	Diff. bet.	Mean	0.0380**	0.0223**	0.0136**	0.0162**	0.0244**
+ Interac.	Q5 and Q1	t-stat.	(6.84)	(13.92)	(8.24)	(2.95)	(4.45)
$Beta_{[-60,-1]}$	Diff. bet.	Mean	0.0380**	0.0306**	0.0211**	0.0076	0.0170**
+ Interac.	Q5 and Q1	t-stat.	(6.84)	(19.17)	(12.68)	(1.36)	(3.07)
$Std_{[-10,-1]}$	Diff. bet.	Mean	0.0380**	0.0239**	0.0170**	0.0145**	0.0211**
+ Interac.	Q5 and Q1	t-stat.	(6.84)	(14.12)	(9.67)	(2.61)	(3.83)

Table 9
Individual Trading after Event Conditional on Earnings Surprise and Pre-Event Return

This table presents analysis of net individual trading in the post-event period conditional on both different levels of abnormal return before the announcement and the extent of the earnings surprise. We construct the net individual trading measure by first computing a daily imbalance measure: subtracting the value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year, and then subtracting the daily mean imbalance over the sample period. Earnings surprise (ES) is defined as the actual earnings minus the earnings forecast one month before the announcement, divided by the price on the forecast day. For the analysis in the table, we sort stocks independently along two dimensions: market-adjusted returns in the three months prior to the announcement ($CAR_{[-60,-1]}$) and ES. We put the stocks into 25 categories: five groups of earnings surprise and five groups of cumulative abnormal returns. We examine net individual trading over two periods: the event window ([0,1]) in Panel A, and the post-event period [2,61]) in Panel B. We implement the Fuller-Battese methodology to correct for clustering, and report the estimated mean with clustering-corrected t-statistics (testing the hypothesis of zero net individual trading). We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Panel A: Net Individual Trading in [0,1] by Earnings Surprise and Abnormal Return in [-60,-1]

		(Negative)		**Earnings Surprise**		(Positive)	Diff. bet.
$CAR_{[-60,-1]}$		Q1	Q2	Q3	Q4	Q5	Q5 and Q1
Q1	Mean	0.0507**	0.0241**	0.0181**	0.0207**	0.0364**	-0.0179
(Negative)	t-stat.	(5.66)	(4.78)	(3.51)	(4.34)	(3.24)	(-1.43)
Q2	Mean	0.0108	0.0084	0.0124**	0.0053	0.0105	0.0000
	t-stat.	(1.59)	(1.86)	(2.83)	(1.03)	(1.04)	(0.00)
Q3	Mean	0.0015	-0.0011	-0.0016	-0.0456	-0.0058	-0.0074
	t-stat.	(0.21)	(-0.26)	(-0.40)	(-0.90)	(-0.64)	(-0.62)
Q4	Mean	-0.0447**	-0.0097	-0.0009	-0.0118*	-0.0166	0.0288*
	t-stat.	(-3.23)	(-1.82)	(-0.18)	(-2.16)	(-1.89)	(2.08)
Q5	Mean	-0.0787**	-0.0319**	-0.0178**	-0.0300**	-0.0573**	0.0169
(Positive)	t-stat.	(-4.79)	(-3.27)	(-3.63)	(-4.91)	(-4.08)	(0.95)
Diff. bet.	Mean	-0.1270**	-0.0560**	-0.0352**	-0.0473**	-0.0953**	
Q5 and Q1	t-stat.	(-8.13)	(-6.16)	(-5.08)	(-7.12)	(-6.66)	

Panel B: Net Individual Trading in [2,61] by Earnings Surprise and Abnormal Return in [-60,-1]

		(Negative)		**Earnings Surprise**		(Positive)	Diff. bet.
$CAR_{[-60,-1]}$		Q1	Q2	Q3	Q4	Q5	Q5 and Q1
Q1	Mean	0.5928**	0.2004**	0.2969**	0.3234**	0.2009	-0.3416**
(Negative)	t-stat.	(8.59)	(4.13)	(5.96)	(6.83)	(1.57)	(-3.34)
Q2	Mean	0.2547**	0.1096	0.1218*	0.0877	-0.0416	-0.3056**
	t-stat.	(3.38)	(1.80)	(2.51)	(1.41)	(-0.52)	(-2.96)
Q3	Mean	0.0868	0.0163	-0.0158	0.0288	-0.2353*	-0.2841**
	t-stat.	(0.97)	(0.25)	(-0.29)	(0.47)	(-2.45)	(-2.88)
Q4	Mean	-0.0784	-0.0110	-0.0183	-0.0925	-0.2222**	-0.1474
	t-stat.	(-0.72)	(-0.16)	(-0.38)	(-1.69)	(-2.72)	(-1.27)
Q5	Mean	-0.3197*	-0.2525**	-0.1822**	-0.2489**	-0.6281**	-0.2802*
(Positive)	t-stat.	(-2.56)	(-3.69)	(-3.20)	(-3.88)	(-7.25)	(-2.36)
Diff. bet.	Mean	-0.9173**	-0.4628**	-0.4703**	-0.5404**	-0.8654**	
Q5 and Q1	t-stat.	(-7.72)	(-6.78)	(-6.46)	(-7.62)	(-8.35)	

Table 10

Regressions Explaining Post-Event Net Individual Trading

This table presents regression analysis relating post-event net individual trading ($IndNT_{[2,61]}$) to past trading, past returns, and the earnings surprise. The dependent variable in the regression is the post-event net individual trading measure ($IndNT_{[2,61]}$), and the regressors include dummy variables for quintiles 1, 2, 4, and 5 of the earnings surprise measure (ES), net individual trading before the event ($IndNT_{[-10,-1]}$ or $IndNT_{[-60,-1]}$), and past abnormal return. To get the ES dummies, we sort stocks into quintiles every quarter on the earnings surprise measure. Earnings surprise (ES) is defined as the actual earnings minus the earnings forecast one month before the announcement, divided by the price on the forecast day. In some of the models we use an alternative measure of earnings surprise: the abnormal return during the event window ($CAR_{[0,1]}$). We construct the net individual trading measure ($IndNT_{[-10,-1]}$ or $IndNT_{[-60,-1]}$) by first computing a daily imbalance measure: subtracting the value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year. We then subtract from the imbalance measure the daily average of individual imbalances over the sample period to get the net individual trading measure, and compute for each stock the cumulative net individual trading measure for these two periods before the announcement. In order to overcome potential econometric problems associated with contemporaneously correlated errors for earnings announcements that are clustered in time, we implement the Fuller-Battese methodology. This approach uses a one-way random effect model in which there is a quarterly effect, and enables us to compute clustering-corrected t-statistics for the coefficients. We use "**" to indicate significance at the 1% level and "*" to indicate significance at the 5% level (both against a two-sided alternative).

Intercept	ES1	ES2	ES4	ES5	$IndNT_{[-60,-1]}$	$IndNT_{[-10,-1]}$	$CAR_{[-60,-1]}$	$CAR_{[-10,-1]}$	$CAR_{[0,1]}$
-0.0217	0.1908**	0.0337	-0.0034	-0.1972**		0.7230**		-1.1909**	
(-0.24)	(4.75)	(0.87)	(-0.09)	(-4.91)		(25.74)		(-9.54)	
0.0082	0.1120**	0.0077	0.0045	-0.1964**	0.1580**		-0.9998**		
(0.09)	(2.78)	(0.20)	(0.11)	(-4.90)	(21.55)		(-17.57)		
-0.0089						0.7506**		-1.4704**	-2.5193**
(-0.10)						(26.82)		(-11.86)	(-16.74)
0.0004					0.1617**		-1.1126**		-2.4293**
(0.00)					(22.18)		(-20.00)		(-16.25)
-0.0068	0.1279**	-0.0005	0.0128	-0.1527**		0.7461**		-1.3697**	-2.3010**
(-0.08)	(3.19)	(-0.01)	(0.32)	(-3.81)		(26.68)		(-10.99)	(-14.95)
0.0247	0.0459	-0.0277	0.0205	-0.1530**	0.1623**		-1.0669**		-2.2939**
(0.28)	(1.14)	(-0.72)	(0.52)	(-3.83)	(22.27)		(-18.81)		(-14.99)

Figure 1
Investor Trading Conditional on Earnings Surprise

This figure presents analysis of net individual and institutional trading on and after earnings announcements conditional on different levels of the analysts' earnings surprise measure. Earnings surprise (ES) is defined as the actual earnings minus the earnings forecast one month before the announcement, divided by the price on the forecast day. We construct the net individual trading measure by first computing a daily imbalance measure: subtracting the value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year, and then subtracting the daily mean imbalance over the sample period. We follow a similar procedure to construct the net institutional trading measure (which excludes dealers and index arbitrageurs). We sort all stocks each quarter according to the earnings surprise and put the stocks in five categories (ES1 contains the stocks with the most negative earnings surprise and ES5 the stocks with the most positive earnings surprise). We then compute for each stock the net investor trading measure for individuals and institutions over certain periods on and after the event. We implement the Fuller-Battese methodology to correct for clustering: for each quintile, we model the net investor trading measure using a one-way random effect framework in which there is a weekly effect (for [0,1] and [2,6]), a monthly effect (for [2,11] and [2,21]), or a quarterly effect (for [2,61] and [0,61]). We plot the estimated means for the most extreme quintiles (bad and good news).

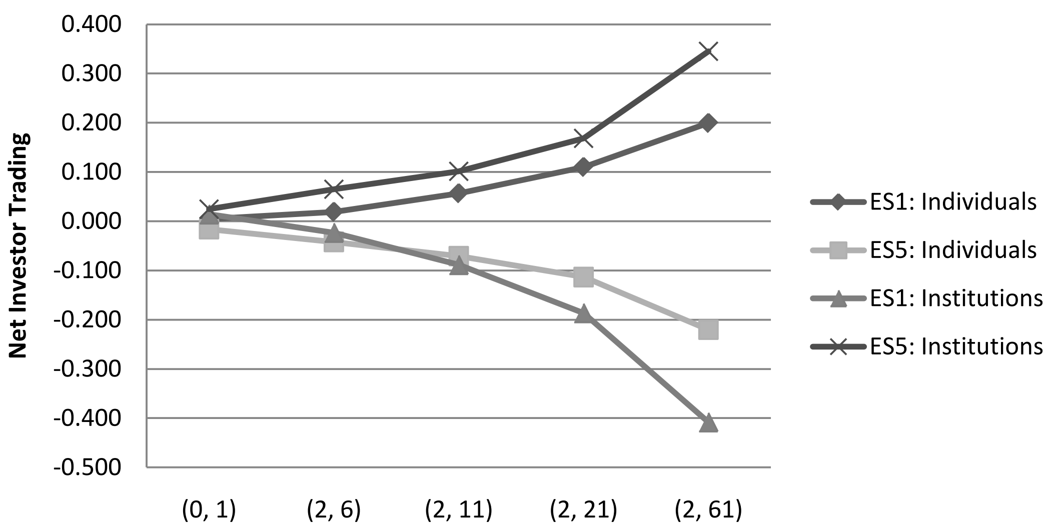

Figure 2

Investor Trading Conditional on Earnings Surprise and Pre-Event Returns

This figure presents analysis of net individual and institutional trading in the post-event period conditional on both different levels of abnormal returns before the announcement and the extent of the earnings surprise. We construct the net individual trading measure by first computing a daily imbalance measure: subtracting the value of the shares sold by individuals from the value of shares bought and dividing by the average daily dollar volume (from CRSP) in the calendar year, and then subtracting the daily mean imbalance over the sample period. The net institutional trading measure is constructed in an analogous fashion. Earnings surprise (ES) is defined as the actual earnings minus the earnings forecast one month before the announcement, divided by the price on the forecast day. For the analysis in the figure, we sort stocks independently along two dimensions: market-adjusted returns in the three months prior to the announcement ($CAR_{[-60,-1]}$) and ES. We put the stocks into 25 categories: five groups of earnings surprise and five groups of cumulative abnormal returns. We then compute for each stock the cumulative net individual and institutional trading measures over the period [2,61]. We implement the Fuller-Battese methodology to correct for clustering. We then plot the estimated means for the net investor trading measures for the extreme analysts surprise quintiles (ES1, bad news, and ES5, good news) and the extreme pre-event return quintiles (CAR1, most negative, and CAR5, most positive). We provide on the figure (next to the columns) the clustering-corrected t-statistics from the Fuller-Battese methodology for the difference between the behavior of investors in ES1 and ES5.