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Abstract

This paper investigates the behavior of individual investors around earnings announcements using a unique dataset of NYSE stocks. We find that intense individual buying (selling) prior to the announcement is associated with significant positive (negative) abnormal returns in the three months following the event. Compensation for risk-averse liquidity provision seems to account for approximately half of the abnormal return, but a significant component remains that could be due to private information or skill. 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 could potentially slow down the adjustment of prices to earnings news and contribute to the post-earnings announcement drift.

I. Introduction

There is a growing body of empirical research that documents the extent to which stock returns are predictable around earnings announcement dates. This research finds that unconditional expected returns are higher around earnings announcements,[1] that characteristics that predict returns unconditionally tend to more accurately predict returns around earnings announcements,[2] and that returns are abnormally high (low) in the months following good (bad) earnings announcements surprises (the "drift").[3] Although the higher risk around earnings announcements is likely to generate some abnormal returns, the degree of return predictability and the magnitude of the post-earnings announcement drift are likely to be due to inefficiencies such as trading-induced frictions.

This paper investigates the trading behavior of individual investors around earnings announcements. Following Kaniel, Saar, and Titman (2008) we explore whether individuals, by acting as contrarians, generate profits by providing liquidity to institutions. In theory, it is possible that because of the higher level of uncertainty, institutions will have a greater need for liquidity around earnings announcement dates, creating greater profit opportunities for individual traders that provide the liquidity. However, it is also possible that the individual investors, who may be naively providing the liquidity, lose money around earnings announcements because of the higher prevalence of informed traders.

We also consider the possibility that there are informed individuals who trade around earnings announcements. Coval, Hirshleifer, and Shumway (2002) claim that individuals are better positioned to exploit a given informational advantage because they typically trade smaller positions and are subject to fewer constraints than institutional investors. However, there will also be more uninformed or irrational trading around earnings announcements if these events attract the attention of individuals who are more

[1] See Chari, Jagannathan, and Ofer (1988) and Lamont and Frazzini (2006).
[2] Jegadeesh and Titman (1993), for example, document high returns around earnings announcements for stocks that have performed well in the previous six months.
[3] The drift was first described in Ball and Brown (1968). See also Foster, Olsen, and Shevlin (1984) and Bernard and Thomas (1989, 1990).

likely to be influenced by behavioral biases (Hirshleifer, Myers, Myers, and Teoh (2002)).

To address these issues we examine the relation between individual investor trades prior to earnings announcements and returns, both on and after the announcements. We find that stocks that individuals bought 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 the two-day event window and 5.45% in the three months after the event. These positive returns, which continue to hold after controlling for past returns and the earnings surprise (relative to analysts' forecast), are substantially higher than the returns following intense individual trading not around earnings announcement dates as shown in Kaniel, Saar, and Titman (2008).

To better understand the determinants of these returns, we provide a decomposition that helps us gauge the extent to which they can be attributed to liquidity provision versus private information. To implement the decomposition we assume that the return associated with a unit of liquidity provision does not change around earnings announcements, but rather what potentially could change is the amount of liquidity demanded. Therefore, we are able to estimate the parameters of the relation between liquidity demanded and returns each day using stocks without earnings announcements. By comparing these regressions in the information rich period prior to earnings announcements to regressions run in the non-event period we conclude that liquidity provision explains roughly half of the abnormal return associated with individual trades prior to the earnings announcement. This suggests that there is still a significant component of the abnormal return (especially in smaller stocks) that is conceivably due to reasons other than liquidity provision, which is consistent with trading on private information or skill.

In addition to examining pre-announcement trading and showing how it relates to announcement and post-announcement returns, we study individual trades on and 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 hypothesis in Hirshleifer et al. (2002), who suggest that individuals are responsible (at least in part) for the post-earnings announcement drift phenomenon. While trading in the opposite direction to the drift may in fact 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.

One of the contributions of our work is to study these questions using a comprehensive dataset that aggregates the executed orders of all individual investors who traded on the NYSE over a four-year period (2000-2003). On this dimension, our research extends prior research that either indirectly infers the trades of individuals based on trade size or looks at a small subset of the market. For example, researchers have used small trades as proxies for the trades of individual investors (e.g., Lee (1992), Shanthikumar (2004), and Frazzini and Lamont (2006)). While such a classification 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 (2007) 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.[4]

Other researchers have used a sample of individuals who traded through one discount broker from 1991 through 1996 (e.g., Hirshleifer, Myers, Myers, and Teoh (2002)). While measuring directly individual trading, this sample is much smaller than the one we are using and looks at a subset of individuals that may or may not be

[4] 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.

representative of the overall population.[5] Finally, Welker and Sparks (2001) and Nofsinger (2001) used the TORQ database to look at individual trading around public announcements, but they do not observe the main results we report (especially the relation between individual trading prior to the event and subsequent returns). While TORQ contains NYSE data similar to ours, it includes only 144 stocks for a three-month period between November 1990 and January 1991. Hence, our different results could be due to the small sample size in the TORQ database or because it contains much older data.

The rest of this paper proceeds as follows. The next section describes the sample and the comprehensive dataset we use. Section III investigates the relation between net individual investor trading prior to the earnings announcements and subsequent returns. An attempt to disentangle two potential explanations for the return patterns we observe is provided in Section IV. Section V examines the behavior of individuals after the announcements. Section VI contains a discussion of the most related papers in the literature, comparing and contrasting our results with prior evidence. Section VII 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

[5] Our dataset contains about $1.55 trillion of individual investor trading in NYSE stocks over four years, compared with $24.3 billion dollar of individual investor trading for the 6-year sample of the discount broker’s clients.

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 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.[6]

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.[7] 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.[8] 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:*

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[6] 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).

[7] 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.

[8] 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.

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

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.[9] 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.

[9] 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.

Lee (1992) and Frazzini and Lamont (2006) find net small trade buying on the 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). 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 possible to that the different small trade pattern is due to the fact that institutions often break up their orders and therefore small trades may come from institutions rather than from individuals. As we mention earlier, Campbell, Ramadorai, and Schwartz (2007) argue that the smallest trades (below $2,000) are more likely to come from institutions. 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.[10] 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 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

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

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.[11] 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 before the Event and Return Predictability

In this section we examine the trading of individuals prior to the earnings announcement and look at the returns of those stocks they intensely buy or sell. To do this 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 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.[12] 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

[11] 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.

[12] 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 examine the post-earnings announcement drift.

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]).[13]

Table 3, which presents our results, 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 accrue to both buying and selling: 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 0.78% abnormal return in the event window and 2.15% up to day 61. The abnormal return on stocks that individuals intensely sold seems to be larger than the abnormal return on stocks that they intensely bought starting one month after the event.[14]

We also sorted the stocks according to size and repeated the analysis separately for three market-capitalization groups: small, mid-cap, and large stocks.[15] For this analysis, we computed 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). In all three size groups the difference between quintile 5 (the stocks that individuals bought) and quintile 1 (the stocks that individuals sold) is highly significant: 8.03% after three months ([0,61]) 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. This is a rather strong and very interesting result, and in the reminder of this section we conduct further analysis to examine its robustness.

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[13] 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).

[14] We find a similar pattern when we sort on net individual trading in the 20 days prior to the announcement.

[15] 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.

In Panel A 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] using the Fuller-Battese methodology with a quarterly clustering correction.

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 for 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.

The picture that emerges from Panel A of Table 4 is that the predictive power of net individual trading remains even when we control for the analysts' earnings surprise measure. This result could suggest that individuals "know" something that is related to the future abnormal return that sell-side analysts do not incorporate in their projections. Alternatively, as discussed in Kaniel, Saar, and Titman (2008), individuals can profit by providing liquidity to other traders that may have an incentive to exit positions prior to earnings announcement dates. In Section IV we will delve deeper into these alternative explanations by decomposing the abnormal return to examine whether individuals indeed seem to be trading on private information.

The next 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 (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 B 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, discounting mean reversion as a potential explanation for the return pattern we document.

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 the earnings surprise (from Panel A of Table 4) and past return (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.[16] 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.

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. Hence, we

[16] 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.

estimate a one-way random effect model with a quarterly effect that enables us to compute clustering-corrected t-statistics for the coefficients.[17]

Table 5 presents the results of the regression analysis. We observe that the dummy variable for ES1 (the quintile of the most negative surprises) has a negative and significant coefficient, while the dummy variable on 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. The predictive power of pre-event net individual trading is not subsumed by the other variables.[18]

IV. Decomposition of the Abnormal Return following Individual Trading

The analysis in Section III 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. What could give rise to these abnormal returns? Theoretical models provide two possible explanations for such 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. This is probably the most straightforward explanation, though it contrasts with the usual tendency to attribute private information or skill to sophisticated institutional investors

[17] 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.

[18] 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.

rather than to individuals. Of course, this interpretation does not require that these investors, as individuals, are particularly well informed. Rather, it is possible that each individual investor has a very small piece of the puzzle and that by aggregating their net trading we in effect create a relatively precise signal that predicts future returns.

The second potential explanation is that these return patterns arise when risk-averse individuals provide liquidity to other traders (e.g., institutions) that may have an incentive to change positions prior to earnings announcements. Theoretical models such as Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993) demonstrate how 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, and then return reversals would manifest themselves in our tests as positive cumulative 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) look at weeks with intense buying and selling by individuals using the same NYSE dataset. While their analysis is unrelated to corporate events (and their findings are robust to eliminating weeks with earnings announcements), they indeed find cumulative abnormal returns of about -0.5% (0.8%) in the two to three months after a week of intense selling (buying) by individuals. They interpret their findings as providing support for the risk-averse liquidity provision models. Here, however, we look explicitly around events that are associated with information and find three-month returns following intense pre-event net individual trading that are about four times larger, suggesting that at least part of the abnormal returns may be related to information rather than just liquidity. To explore this possibility, we provide a test that attempts to decompose the cumulative abnormal returns we observe following individual buying and selling into a component that is attributed to risk-averse liquidity provision and a component that is attributed to trading on private information or skill.

In order to decompose the abnormal return, we need to impose some structure on the return generating process. After all, we do not have a direct way to observe the private information or assess the skill that individuals actually possess. Our method assumes that the "market price" of liquidity provision is the same irrespective of whether a stock has an earnings announcement or not. We allow the total compensation for liquidity provision (i.e., price of liquidity provision times quantity of liquidity demanded) to change around earnings announcements in that the amount of liquidity demanded we use is taken from the actual event. In our empirical specification, we use the actual net individual trading prior to each earnings announcement to tell us how much liquidity is demanded from individuals. We measure the compensation for liquidity provision simply in terms of abnormal return on and after the announcement. To estimate the parameters of the function that relates net individual trading to future abnormal returns (the "market price of liquidity provision") every day we use stocks that do not have earnings announcements, and hence we are guaranteed that this market price of liquidity provision is not contaminated by trading on private information about the earnings announcement.[19] We then use the parameters we estimate from stocks without announcements together with the actual magnitude of pre-event net individual trading for each announcement to get an estimate of the expected abnormal return due to liquidity provision.

The return component attributed to information or skill is computed by subtracting the estimated expected abnormal return (due to liquidity provision) from the actual abnormal return following each announcement. This means that what we attribute to information or skill is the portion of the abnormal return that we cannot explain based

[19] If there is a small amount of individual investor trading on private information even on dates without earnings announcements, our procedure would lump it together with liquidity provision, and the abnormal return component we attribute to private information about the earnings announcement would only reflect the return predictability in individual trading over and above its magnitude on regular days.

on the structure we impose on liquidity provision. The estimate we obtain is an improvement over simply attributing all the abnormal return to information trading in that we remove the component that we believe to be a reasonable estimate of the compensation individuals would get for accommodating the demand for immediacy of other traders.

The specifics of our methodology 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:

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

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

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 return for each day in the sample period.

Say we want to compute the expected abnormal return due to liquidity provision for an earnings announcement on April 3rd, 2001. 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 ($\mathrm{IndNT}^{i}_{[3/20/01,4/2/01]}$ and $\mathrm{CAR}^{i}_{[3/20/01,4/2/01]}$), we compute the expected abnormal return according to Model 1 as follows:

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

A similar construction produces the estimate $\mathrm{ECAR2}^{i}_{[4/3/01,6/27/01]}$ using the parameters estimated from Model 2 and actual net individual trading and return in the 60 days prior to the earnings announcement. 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

$CAR_{[0,61]} - ECAR1_{[0,61]}$ (or $CAR_{[0,61]} - ECAR2_{[0,61]}$) as the abnormal return component that cannot be attributed to liquidity provision and hence is attributed to private information or skill.

The results of this analysis 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 the same way we constructed Table 3. The first column of Panel A of Table 6 shows $CAR_{[0,61]}$ 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 and ECAR2 from Model 2) 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 some 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 probably due to risk-averse liquidity provision while the other half is due to information or skill.

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 reported in the previous section, 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-return/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-return/past-trading window of 10 days) provides evidence of a significant information or skill component for small stocks but not for the larger stocks. It is conceivable that individuals would more likely have insights that sell-side analysts do not posses about smaller firms than about larger firms. For example, the smaller firms could be regional firms with which the individuals are more intimately familiar. They could therefore use their knowledge of these firms to get out of positions when they think that adverse news is about to become public, giving rise to at least a portion of the abnormal return we observe following individual trading.[20]

We note, though, that our results are obtained by imposing the assumption that the functional form of the relation between liquidity provision and future return remains the same around events. If one were to believe that this function changes, or that it is likely to change for smaller stocks but not for larger stocks, our estimate of the component of the abnormal return attributed to information or skill would be somewhat overstated.[21]

V. Investor Trading after the Event

While the previous sections focused on the behavior of individuals prior to earnings announcements, in this section we look at their trading during and after the event. The reason to focus on their behavior after the event is that one of the puzzles associated with earnings announcements is the "drift," which is the phenomenon that stocks with

[20] The different results obtained from Model 1 and Model 2 could simply reflect a tendency of individuals to trade on information earlier (e.g., a month before the event) rather than wait for the last two weeks before the event.

[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 explain 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.

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 (2002) hypothesize that if the drift reflects mispricing, 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 naïve 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 a discount broker, but conclude that their data does 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).[22] 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 the net individual trading measure in Section II.A. Institutions seem to behave in a "news-momentum" manner: they sell after bad news and buy the stocks following good news.

[22] The differences in the net 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.

The patterns in Figure 1 seem consistent with the idea that individuals trade in the direction that would slow down the adjustment of prices to the news after earnings announcements. 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 differentiate 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: earnings surprise and 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.[23] Panel A of Table 7 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 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). In other words, during the event individuals simply behave as contrarians.

Panel B of Table 7 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

[23] 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 also using three months of return 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.

(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 8 provides another robustness test for the news-contrarian effect that we document for the individuals. We carry out a regression analysis where 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. 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 first measure of earnings surprise we use is the analysts' earnings surprise (ES) dummies as in Table 5. The second measure we use 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 as "contrarian" (i.e., as a response to prices rather than news) 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.

The results in Table 8 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 pattern we identify where individuals trade after the event in opposite direction to the news has the potential to impede the adjustment of prices to the news. In fact, combining the results in Sections III and V 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 (or sustain) the drift. Unfortunately, our data do not enable us to identify specific individual investors and observe their strategies. 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.[24] It is, however, consistent with the relationships between return and trading that we observe.

VI. Our Findings in the Context of the Literature

In this section we relate our results to the existing literature on buying and selling by individuals around earnings announcements.[25] Our main result in Section III demonstrates that when individuals intensely buy (sell) prior to earnings announcements, stocks experience large positive (negative) abnormal returns on and after the events. This result, to the best of our knowledge, has never been documented for stocks in the U.S. Welker and Sparks (2001) look at the behavior of individuals around various public announcements from November 1990 through January 1991 using the TORQ database.[26] They do not find a consistent relation between the market reaction at the time of the announcement and the direction of trading by investors before the news release. The TORQ database contains data from the NYSE's CAUD files that is similar to the data we use here, but it is a substantially smaller dataset (with only 82 earnings announcements compared with 17,564 announcements in our sample), which may not provide enough power to detect the abnormal returns.

Vieru, Perttunen, and Schadewitz (2004) investigate the trading of individual investors on the Helsinki Stock Exchange around interim earnings announcements. 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

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[24] 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 (both a positive earnings surprise and a positive abnormal return) in the post-event period show a pattern of individual investor buying prior to the announcement and selling after the announcement.

[25] While our focus is on the directional trading (buying and selling) by 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).

[26] Nofsinger (2001) also uses TORQ to investigate individual trading around a variety of firm-specific and macro-economic announcements.

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.

Our main result in Section IV is that a portion of the abnormal return we detect subsequent to pre-event individual investor trading cannot be explained by risk-averse liquidity provision, and therefore could arise from trading on private information or skill. The issue of trading on information/skill is not emphasized by most other papers in the literature on individual investors because they report either a negative relation or no relation between trading by individuals and future return (see, for example, Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2000), and Griffin, Harris, and Topaloglu (2003)). An exception is a paper by Coval, Hirshleifer, and Shumway (2002). They suggest that individual investors are better able to exploit their private information because they are small relative to institutions, and look for evidence in the 1991–1996 discount broker dataset (though not specifically around earnings announcements). They document persistence in the performance of some individual investors, and while on average individuals in their sample underperform, they document that some traders earn 12-15 basis points per day in the week after they trade.

Our main result in Section V is that individuals trade in a news-contrarian fashion after earnings announcements, and hence their trading could be related to the drift phenomenon. This result is stronger than previous U.S. evidence. In particular, Hirshleifer, Myers, Myres, and Teoh (2002) use a sample of clients of one discount broker from 1991 through 1996 to test the hypothesis that naïve individual investors would trade in 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, consistent with helping to create a drift by slowing down the adjustment of prices. However, this is not mirrored by individual selling after positive earnings surprises, and they end up concluding that their evidence does not support the hypothesis that individual investors drive the post-earnings announcement drift.[27]

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.[28] Our results on the behavior of individuals in the post-event period in the U.S. are 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.[29]

VII. Conclusions

In this paper we investigate the relationship between net trading of individual investors around earnings announcements and return patterns. Our results provide answers to some questions, but in turn raise additional questions that we hope future work will address. The three main insights that arise from our work is that (i) net individual trading prior to earnings announcements predicts abnormal returns on the announcement date as well as in the post-event period, (ii) not all of the return predictability could be attributed to risk-averse liquidity provision, and hence some of it could possibility be due to trading on private information or skill, and (iii) individuals in the U.S. exhibit news-contrarian trading behavior following earnings announcements that could inhibit the adjustment of prices to information.

[27] 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 naïve 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.

[28] 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.

[29] 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.

Starting with the relation we observe between pre-event individual investor trading and returns, it is possible that individuals simply buy (sell) when other traders push prices down (up), and hence benefit from the subsequent reversion in prices. This is essentially the argument made by Kaniel, Saar, and Titman (2008) who find that net individual trading has predictive power with respect to short-horizon return, and who interpret this return pattern as arising from risk-averse liquidity provision on the part of individuals (in the spirit of the theoretical models of Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993)). An alternative explanation is that individual investors who trade on the NYSE have useful information about stocks (either private information or skill in interpreting public information), and are therefore able to forecast the response of the stocks' prices to the new information that is revealed in the earnings announcements. To gain insights into the relative importance of these two explanations, we impose a structure that enables us to decompose the abnormal return into separate components that we attribute to liquidity provision and information/skill. Our findings seem to suggest that both explanations may be at work.

After the announcements, individuals exhibit both contrarian and news-contrarian behavior. Both of these tendencies can be driven by liquidity provision because other traders (especially institutions) could pursue momentum and news-momentum trading. Hence, individuals could be responding to the other traders' needs, and as such their news-contrarian behavior may seem a bit naïve. This is the argument that Hirshleifer et al. (2002) use when they discuss the hypothesis that individual investors generate the drift by trading in opposite direction to institutions. Their characterization as naïve is based on the fact that stocks exhibit a drift, and hence trading in the opposite direction would imply that individuals must lose to institutions.

However, it could be that the individuals' trading pattern after the announcement is evidence of profit-taking behavior. This would tie their predictive ability before the events to their contrarian trading after the event. In other words, they could simply be profitably reversing positions to which they have entered prior to the announcements, hence reducing their risk after the events. Such behavior is consistent with the theoretical work of Hirshleifer, Subrahmanyam, and Titman (1994). In their model, lucky or skillful investors uncover valuable information early, while unlucky or low-ability investors uncover it only later. In equilibrium, investors who discover the information early trade aggressively initially and then partially reverse their trades. Prices continue to adjust to information in the late trading round (hence creating a drift) due to the trading of those investors who become informed late. The strategy of the early-informed traders appears to exhibit a "profit-taking" property.

Could individual investors be these early-informed traders? It is hard to say. This interpretation is somewhat counter-intuitive given the vast resources institutions devote to gathering information. However, there are reasons to believe that while each individual could be less informed than an institution, the aggregated trades of individuals would be more informative than institutional trades. First, as we mentioned earlier, it is possible that although each individual investor has a very small amount of information, when this information is aggregated through the trades of many individuals the resulting signal can be relatively precise. This might be particularly true around earnings announcement dates if institutions are averse to trading too aggressively immediately before an announcement for fear of litigation. Second, Coval, Hirshleifer, and Shumway (2002) claim that individuals may be better positioned to trade aggressively because it is easier to buy or sell small quantities of shares, and individuals may also be less constrained than a typical mutual fund (at least with respect to diversification requirements or short-selling).

However, while our comprehensive dataset of individual investor trading enables us to document these interesting patterns and provide new insights, it does have 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 naïve 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 need to await additional datasets.

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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. 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). 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					
$IndNT_{[-10,-1]}$		[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)

Table 4
Returns Following the Event Conditional on Past Information

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 the extent of earnings surprise (in Panel A) or past return (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 quintiles on the earnings surprise measure (ES), and within each quintile we sort on net individual trading before the event ($IndNT_{[-10,-1]}$) (resulting in 25 categories). We then compute for each stock the cumulative market-adjusted return in [0,61]. 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 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 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 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 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)	

Panel B: 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)	

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. 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. 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 additional control variables (contemporaneous net individual trading 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 certain periods before, during, and after the announcement.. 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:

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

A similar construction produces the estimate $\text{ECAR2}^{\text{i}}_{[0,61]}$ 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 estimates 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. For 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: 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.	Mean	0.0545**	0.0290**	0.0221**	0.0255**	0.0323**
Q5 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)

Table 7
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 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 on [-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 on [-60,-1]

		(Negative)		**Earnings Surprise**		(Positive)	Diff. bet.
$CAR_{[-60,-1]}$		Q1	Q2	Q3	Q4	Q5	Q5 and Q1
Q1	Mean	0.5958**	0.1784**	0.2653**	0.3230**	0.0492	-0.3432**
(Negative)	t-stat.	(7.90)	(2.69)	(3.99)	(6.13)	(0.19)	(-3.34)
Q2	Mean	0.2592**	0.1153	0.1094	0.1055	-0.0415	-0.3021**
	t-stat.	(2.59)	(1.46)	(1.70)	(1.26)	(-0.51)	(-2.93)
Q3	Mean	0.1117	0.0262	-0.0208	0.1904	-0.2621*	-0.2899**
	t-stat.	(1.02)	(0.31)	(-0.36)	(1.37)	(-2.33)	(-2.92)
Q4	Mean	-0.0810	-0.0354	-0.0381	-0.0912	-0.2225*	-0.1356
	t-stat.	(-0.53)	(-0.33)	(-0.59)	(-1.24)	(-2.09)	(-1.18)
Q5	Mean	-0.3490*	-0.2550**	-0.1943**	-0.2698**	-0.5954**	-0.2385*
(Positive)	t-stat.	(-2.39)	(-3.30)	(-2.96)	(-3.28)	(-5.55)	(-2.00)
Diff. bet.	Mean	-0.9284**	-0.4566**	-0.4743**	-0.5524**	-0.8304**	
Q5 and Q1	t-stat.	(-7.77)	(-6.73)	(-6.49)	(-7.79)	(-8.05)	

Table 8

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. 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. 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. In some of the models we use an alternative measure of earnings surprise: the abnormal return during the event window ($CAR_{[0,1]}$). 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 ($IndNT_{[-10,-1]}$ 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 over certain periods before the announcement. 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).

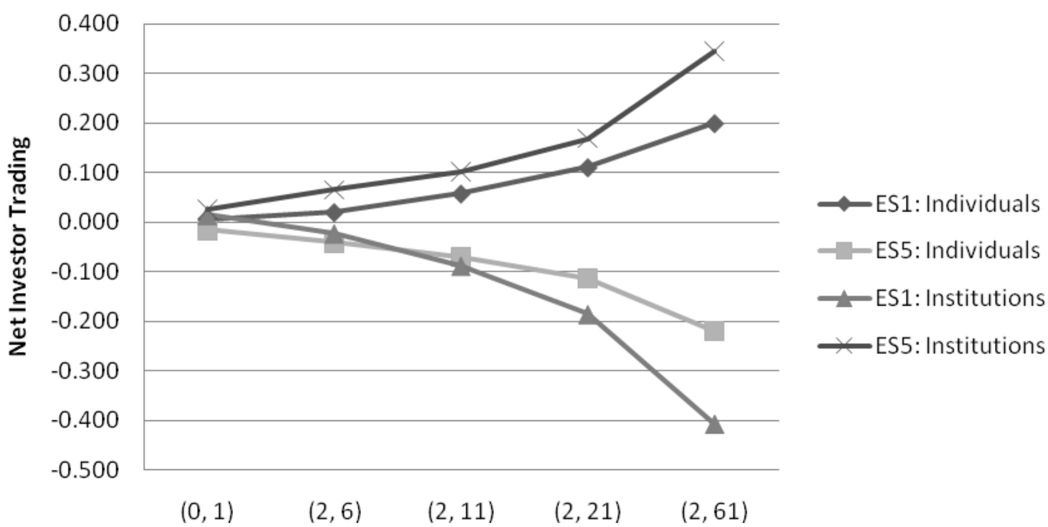

Figure 2

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 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.