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Abstract

In this paper, we infer motives for trade initiation from market sidedness. We define trading as more two-sided (one-sided) if the correlation between the numbers of buyer- and seller-initiated trades increases (decreases), and assess changes in sidedness (relative to a control sample) around events that identify trade initiators. Consistent with asymmetric information, trading is more one-sided prior to merger news. Consistent with belief heterogeneity, trading is more two-sided (1) before earnings and macro announcements with greater dispersions of analyst forecasts and (2) after earnings and macro news events with larger announcement surprises. A simultaneous equation system is used to examine the co-determinacy of sidedness, the bid-ask spread, volatility, the number of trades, and the order imbalance.

Key words: sidedness, divergent beliefs, trade initiation, trading motives, earnings news, macro news

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A trade is initiated in a continuous limit order book or quote driven market whenever a relatively impatient participant submits a market order that meets or crosses a price that has previously been posted by a more patient participant (a limit order trader or dealer). The trade initiator is demanding immediacy and certainty of execution, and is forgoing the possibility of achieving a better price. The literature suggests that the impatience which underlies trade initiation is due to the short-lived nature of any information advantage. A trade initiator may also be experiencing a shock to his or her impatience (e.g., as the end of a trading day approaches), or be responding to a temporary decrease in the price of immediacy (as occurs, for instance, when the limit order book thickens). In this paper, we analyze buyer-initiated and seller-initiated trades in brief time intervals (five minutes) around different information events (e.g., earnings reports) and during the opening and closing minutes of days without news. In so doing, we are able to draw inferences on the motives for trade initiation, the objective of this paper.

Empirical market microstructure research has sought to identify trade initiators from the interaction between price formation and indicators of trading activity, including the number and sign of trades, trade size, and the duration between trades. A large literature focuses on identifying trading driven by information asymmetries. Major efforts include Hasbrouck (1991) who shows that market makers, by observing trade attributes such as sign and size, can infer information from the trade sequence. Easley, Kiefer and O'Hara (1996, 1997a, 1997b), based on an asymmetric information model, estimate the arrival rates of informed and uninformed traders using data on the daily numbers of buyer-initiated and seller-initiated trades, and no-trade outcomes. Dufour and Engle (2000) find that trades cluster together in time as insiders trade quickly to preempt information leakage. More recently, attention has also turned to the demand for immediacy by liquidity traders. In particular, Tkatch and Kandel (2006) present evidence that traders offer price concessions to obtain more immediate executions, and that such behavior has a significant effect on high frequency market dynamics.

We also focus on identifying trade initiators. Our objective is to disentangle evidence of trade initiation triggered by asymmetric information (i.e., some investors are better informed than others), and by differential information or beliefs (i.e., investors have different information or interpret the same information differently). To this end, we introduce a measure of market sidedness that we define as the correlation between the numbers of buyer-initiated trades and seller-initiated trades in brief time intervals. An increase (decrease) in the correlation indicates a more two-sided (one-sided) market condition. We analyze changes in sidedness by contrasting the correlation observed in a specific information environment (e.g., before earnings or macro announcements) with the correlation observed in non-news days.

Based on a discussion of models of trade initiation in Section I, we argue that trading motivated by asymmetric information generates more one-sided markets, whereas trading motivated by differential information and/or beliefs leads to more two-sided markets. Using a matched sample of 41 New York Stock Exchange (NYSE) and 41 Nasdaq stocks, our analysis of five-minute trading intervals indicates that trade initiation is attributable to each of the above noted factors. We present evidence of more one-sided trading prior to merger news; one might infer that at least some of these same-side trades are motivated by asymmetric information. Trading is more two-sided before earnings and macro news announcements when the dispersion of analyst forecasts is large, which is consistent with trade initiations attributable to differences in opinions. Finally, more two-sided markets are observed after news releases, especially when the news surprises are large, consistent with trades being driven by investors who acquire diverse information in order to better interpret the news (as in Kim and Verrecchia (1994)).

Research on earnings announcements show that trading is stimulated by differences in opinions (Kandel and Pearson (1995); Bamber, Barron and Stober (1999); Diether, Malloy and Scherbina (2002); Sadka and Scherbina (2007)) and differential information acquisition (Krinsky and Lee (1996); Barron, Byard and Kim (2002)). Our findings on sidedness underscore the importance of these motives for a variety of news events (earnings, macro and merger news).

To obtain further insights into trade initiators, we examine whether sidedness determines market dynamics, by sorting stocks into two groups based on their "excess" sidedness (relative to the average sidedness in the no-news sample). Before news, we find higher volatility and more trades, and lower order imbalance, for more two-sided stocks and also for news with greater analyst forecast dispersions. A similar pattern exists after news releases for more two-sided stocks and also for larger news surprises. These results show that greater differences in opinions or information are associated with increased volatility and trading, consistent with Grundy and McNichols (1990), Harris and Raviv (1993), Shalen (1993), Kandel and Pearson (1995), He and Wang (1995), Hong and Stein (2003), and Banerjee and Kremer (2005).

We employ a simultaneous equation system to study the endogeneity of sidedness (e.g., changes in sidedness may result from a temporary decrease in the cost of immediacy). We find that sidedness, effective spreads, order arrivals, and volatility are co-determined around news events for Nasdaq stocks as well as for the no-news sample. There is also robust evidence of a significant association between sidedness, forecast dispersions and news surprises.

In addition to news-related changes in sidedness, an exogenous increase in the proportion of impatient buyers and sellers may also trigger more two-sided trading. We observe high immediacy demand for Nasdaq stocks compared to NYSE stocks in the first 5 minutes on days without news. Since, in our sample period, NYSE had an opening call but Nasdaq did not, the result is consistent with a reduction in impatience following the call auction (Bosetti, Kandel and Rindi (2006)). We further observe more two-sided trading for Nasdaq stocks in the last 5 minutes on days without news; the more two-sided Nasdaq stocks have greater volatility and trades, and lower spreads. These results are consistent with the theoretical predictions of Foucault, Kadan and Kandel (2005) and Rosu (2006), and complement evidence by Tkatch and Kandel (2006) that liquidity traders demand immediacy in the Tel Aviv Stock Exchange.

Sidedness is related to order imbalance: we find that more two-sided markets are generally, but not always, associated with lower imbalance.[1] However, forecast dispersions and news surprises are not significantly related to imbalance, suggesting that belief heterogeneity is reflected in sidedness rather than in imbalance. Since sidedness and order imbalance are informative of each other and of market dynamics, we conclude that sidedness and imbalance incorporate different (and complementary) information.

As robustness tests, we delete executions inside the quotes and at mid-quotes (where errors in the Lee and Ready (1991) algorithm for classifying buyer and seller initiated trades are most likely to occur). Our findings continue to hold and, in some cases, are even stronger. Next, we examine the absolute volume imbalance as a measure of sidedness in order to better capture the effect of large institutional trades. We find that institutions when trading in NYSE stocks appear to be more impatient in the closing minutes compared to retail traders.

We contribute to the literature by introducing a new liquidity measure (i.e. sidedness) that allows us to derive sharper predictions about market behavior. The sidedness measure enables us to better distinguish between alternative trading motives. For example, trading motivated either by asymmetric information or by heterogeneous beliefs gives rise to high volatility, but the former results in one-sided markets whereas the latter gives rise to two-sided markets. Indeed, the results indicate that belief heterogeneity is mainly reflected in our sidedness measure, rather than in alternative measures such as the order or volume imbalance. Hence, sidedness may be a useful measure when analyst dispersion data is either unavailable or uninformative.

Accounting for sidedness is important for studying the impact of news since forecast dispersions and news surprises affect volatility and spreads directly as well as indirectly via their effects on sidedness. Moreover, sidedness may have predictive power for market dynamics (more two-sided trading appears to predict higher volatility and trades, and lower spreads).

The sidedness measure also sheds light on belief convergence. The literature on earnings announcements has examined how quickly the mispricing of stocks with high analyst disagreements is corrected (e.g. Sadka and Scherbina (2007)). We show that, when the sidedness measure diverges, *post-news* differences in liquidity, volatility and trading activity between small and large *pre-news* forecast dispersions are generally significant. Conversely, when sidedness converges, post-news differences in liquidity, volatility and trading activity are not significant for small and large pre-news dispersions. This suggests that convergence or divergence in sidedness is indicative of convergence or divergence in beliefs.

The paper is organized as follows. In Section I, we discuss models of trade initiation, their predictions for sidedness and market dynamics, and events likely to identify trade initiators. In Section II, we describe our data. In Section III, we present descriptive statistics and in Section IV, we estimate sidedness around news events. In section V, we examine market dynamics for stocks sorted by sidedness. In Section VI, we present results from the simultaneous equation regressions. In Section VII, we study the opening and closing minutes of trading on days without news. In Section VIII, we conduct robustness checks. We conclude in Section IX. All results that are not reported in this paper are available from the authors on request.

I. Sidedness, Trade Initiation and Market Dynamics: Predictions and Identifying Events

Agents who submit orders that trigger trades are demanding immediacy of execution at the expense of price improvement.[2] The literature suggests that such behavior results from temporarily high impatience due to the short-lived nature of any information advantage, or from an aggregate shock to traders' impatience. When information is involved, the sidedness of markets depends on whether it is asymmetric (i.e., some information is superior to others), or differential (i.e., either the information is different or news is interpreted differently). We consider each of these effects separately in Table I. The first column of the table identifies the trading motive, the second column lists scenarios likely to be associated with these motives, and the remaining columns summarize the implications of the motives for sidedness and four market quality variables – price volatility, trading costs, number of trades, and order imbalance.

INSERT TABLE I HERE

A one-sided market is likely to occur when some investors have superior private information (Wang (1994); Llorente et al. (2002)).[3,4] Volatility increases under one-sided conditions because less-informed investors demand a larger premium to trade against better-informed participants and, consequently, prices become more responsive to supply shocks (Wang (1993, 1994)). Greater volatility and adverse selection imply that trading costs are also higher with asymmetric information. A greater order imbalance is apt to ensue as trades occur predominantly on one side of the market while the effect on volume is ambiguous.[5]

Information-motivated trading can be triggered on both sides of the market when investors observe different information signals (He and Wang (1995)) or interpret an ambiguous signal differently (Harris and Raviv (1993); Kandel and Pearson (1995)).[6] Dispersed beliefs or information are likely to be associated with higher volatility and a larger number of trades. For example, Grundy and McNichols (1990) and Shalen (1993) show that dispersed opinions magnify the effect of noisy information on price changes. However, the effect on trading costs is unclear. On the one hand, greater uncertainty about a stock's value decreases liquidity (He and Wang (1995)). On the other hand, two-sidedness imply that dealers and limit order traders are at lower risk of incurring unbalanced inventory or portfolio positions, which increases liquidity.

A shock to traders' impatience may also increase the demand for immediacy (Foucault, Kadan and Kandel (2005); and Rosu (2006)).[7] Foucault, Kadan and Kandel (2005) consider an increase in the proportion, p, of impatient traders. Abstracting from informational effects, they show that the bid-ask spread and trading activity increases. There is more trading because the probability that a trader will submit a market order increases with p. Due to the high arrival rate of market orders, limit order traders post less aggressive limit orders, and spreads widen (as also considered in Cohen et al. (1981)). Volatility is also likely to be higher when traders demand more liquidity. We expect that impatient traders will commonly place orders on both sides of the market, and so two-sidedness is likely to increase in p.

The second column in Table I lists scenarios likely to identify trading motives. One-sided markets driven by asymmetric information are likely prior to private news events (e.g. merger news) if the information leaks out. Two-sided markets are likely before scheduled news releases (e. g. earnings reports) with high analyst forecast dispersions which may be viewed as proxies for differences of opinions among investors (Diether, Malloy and Scherbina (2002)). Two-sided markets due to differential information may occur after large news surprises as investors acquire diverse information to interpret the events (Kim and Verrecchia (1994)).

We further identify immediacy-based trading around liquidity events: the opening and closing minutes of days without news. In our sample period, Nasdaq did not have an opening auction whereas the NYSE did. Since the proportion of impatient traders is likely to be smaller after an auction (Bosetti, Kandel and Rindi (2006)), differences in sidedness during the opening sessions of the NYSE and Nasdaq markets may indicate differences in the demand for immediacy in the two markets. Temporary increases in the demand for immediacy may also occur towards the end of the trading day (Cushing and Madhavan (2000); Tkatch and Kandel (2006)); two-sided markets will result if impatient participants arrive as both buyers and sellers.

Each of the scenarios mentioned above is likely to prevail in reality, depending on the source and nature of the shock to immediacy. We estimate patterns of sidedness, volatility, trading costs, the number of trades and order imbalance for each scenario. Our objective is to infer the existence of each of the underlying trading motives from these patterns.

II. Data

We use time-stamped trade and quote data from the Transactions and Quotes (TAQ) Database of the NYSE, which records the price and quantity of trades, and dealer quotes. The data are from January 2, 2003 to May 28, 2003, for a matched sample of 41 NYSE stocks and 41 Nasdaq stocks.[8] On January 2, 2003, market capitalization and the closing price averaged $4.7 billion and $21.56 for NYSE stocks, respectively, and $4.4 billion and $21.35 for Nasdaq stocks, respectively (the two markets have similar values as the samples are matched according to these variables). To purge the data of potential errors, we delete trades or quotes with:

1. Zero or missing trade price.
2. Quotes that are missing, negative or unusually small relative to surrounding quotes.[9]
3. Bid (ask) quotes that change from the previous bid (ask) quote by more than $10.

4. The quoted bid-ask spread is negative.
5. The proportional quoted bid-ask spread or effective bid-ask spread is in the upper 0.5 percentile of its distribution by stock and time interval.
6. The quoted bid or ask size is negative.
7. Trade or quote prices that are outside regular trading hours.

These filters eliminated approximately 3% of all recorded prices and quotes. After elimination, the NYSE data include 4,877,678 trades and the Nasdaq data include 10,860,576 trades. The trading day is divided into 5-minute intervals. The number of 5-minute intervals in the final sample is 318,704 intervals for NYSE stocks and 318,468 intervals for Nasdaq stocks.

We use the Lee and Ready (1991) algorithm to identify transactions as either buy-triggered or sell-triggered. If the trade price is closer to the most recent ask (bid) price in the same stock, it is a buyer (seller) initiated trade. For prices equal to the quote mid-point, trades that take place on an up tick are buys, and trades that take place on a downtick are sells.[10] We examine the effects of trade classification errors on our results in Section VIII.

To identify the source of a change in the demand for, or the cost of, immediacy, we examine trading around earnings reports, macroeconomic releases scheduled for 8:30 AM, and corporate restructuring (CR) news. (We study liquidity events in Section VII). Quarterly earnings report dates, actual earnings per share (EPS), and analysts' most recent forecasts of quarterly EPS are taken from the I/B/E/S database. Data for announcements of Employees on Nonfarm Payroll, Core CPI and Producer Price Index are from the Haver database. Prior studies (e.g. Fleming and Remolona (1999)) show that these three macro releases (about a quarter of all 8:30 AM announcements) have the most significant market impact. CR news days are identified by searching major publications for news related to M&A, share buybacks, divestitures, and joint ventures. Prior research shows significant stock price movements around these corporate events.

Trading motives are likely to be different before and after news releases. We create a "*Before*" sample that consists of the two days before earnings, macro, or CR news. For earnings and macro news, we further divide the "*Before*" sample by the standard deviation (SD) of analyst forecasts, a measure of disagreement. In order to compare the SD for different earnings (macro) reports, we divide the SD by the absolute value of the mean (median) forecast.[11] The upper 50 percentile of standard deviations are taken to be *large dispersions*; the remaining forecasts are *small dispersions*. Focusing on large versus small dispersions is in accord with Banerjee and Kremer (2005), who show that observed volume patterns are best explained by the existence of infrequent major disagreements among agents.

We also create an "*After*" sample consisting of the day of the earnings, macro, or CR news, and the following day. For earnings and macro news, we further divide the "*After*" sample according to whether the news surprise is large or small. Foster and Viswanathan (1993) show that volatility and trading volume depend on the news surprise. To compare earnings surprises across stocks, we scale it by the SD of surprises for the stock. Similarly, to compare surprises across different macro announcement types, we follow Balduzzi, Elton, and Green (2001) and scale it by the SD of surprises for the announcement type. Thus, the surprise $S_{k,t}$ for an announcement type k or for an earnings report for stock k on day t is:

$$S_{k,t} = \frac{R_{k,t} - M_{k,t}}{\sigma_k} \qquad (1)$$

where $R_{k,t}$ is the actual EPS or the first-reported macro release, $M_{k,t}$ is the median analyst forecast, and σ_k is the SD of surprises for stock k or announcement type k. *Large* surprises are in the upper 50 percentile of the surprise distribution; the remaining surprises are *small surprises*.

The three news events differ by how much they can be anticipated, and also whether they relate to private or public variables. Macro announcements are always scheduled for release on specific days and times and relate to public information such as inflation. Earnings report dates are generally, but not always, predictable whereas CR news is mostly unanticipated; moreover, earnings and CR news are about individual firms. We expect that trading based on asymmetric information is likely to be least before macro news and most before CR news. We further expect trading based on heterogeneous beliefs around earnings and macro news when analyst forecast dispersions or news surprises are high.

We study only the first 15 minutes of days around news events to capture the immediate impact of the news. The impact of macro releases lasts 30 minutes or less (Green (2004)). Since major news reports are often released during the overnight period, the first 15 minutes are likely to capture the immediate effects of earnings and CR news as well. The short term period also serves to filter out trading unrelated to news (e.g. follow-on trading by noise traders).

We compare sidedness around news events with a control sample (called *no-news* days) constructed to exclude the effect of news to the extent possible. Specifically, we remove the 2 days before and the 2 days after earnings, macro and CR news days. To further mitigate any news impacts, we also exclude *high return* days which we define as the 30% of days with the highest absolute value of a stock's close-to-close excess returns.[12] The S&P 500 (Russell 2000) returns are used to compute the excess returns for the NYSE (Nasdaq) stocks.

III. Descriptive Statistics around News Events

In this section we describe patterns of volatility, liquidity, and trading activity on days surrounding news events. Referring to Table I, if trades are based on asymmetric information, we expect high levels of trading costs, volatility and order imbalance. If trading is motivated by differential information or beliefs, we continue to expect high volatility but not necessarily high trading costs; further, trading activity should be high and the order imbalance relatively low. We employ the following measures for the analysis. Volatility is *HILO* minus 1, where *HILO* is the ratio of the maximum to the minimum price in a period. Trading cost is *PEBAS*, the proportional effective half-spread, defined as $Q(P\text{-}M)/M$, where M is the quote mid-point, P is the trade price, and Q is +1(-1) for buyer (seller) initiated trades. The absolute order imbalance, *AIMB*, is the absolute value of (*BUY–SELL*)/*NTR*, where *BUY* (*SELL*) is the number of buyer (seller) initiated trades and *NTR* is the total number of trades.

INSERT TABLE II HERE

In Table II, we present descriptive statistics for the first 15 minutes of no-news days and around news events. Results of no-news days are repeated for each of the three news events for convenience. The reported values for *HILO*, *PEBAS*, and *AIMB* are each multiplied by 100. We compare the mean and median values (using the Wilcoxon z statistic) between days with and without news. The entries ** and * denote differences that are significant at, respectively, the 1% and 5% levels or less.

Before earnings reports, the various measures are not statistically different for news and no-news days in either market. Following earnings reports, volatility, *NTR* and the median bid-ask spread are all higher while, in both markets, the absolute imbalance is lower. Prior to macro announcements, volatility is higher for Nasdaq stocks and the bid-ask spread is higher for NYSE stocks compared to non-news days. Following macro announcements, volatility and the spread are higher in both markets, in line with previous research. Further, *NTR* increases for Nasdaq stocks. Before CR news, the median bid-ask spread is higher and *NTR* lower for NYSE stocks, while the spread is lower and *NTR* is higher for Nasdaq stocks (compared to non-news days).

We observe the same pattern after CR news: the median spread increases and *NTR* falls compared to no-news days for the NYSE stocks, while the reverse is true for the Nasdaq stocks.

In summary, volatility, the bid-ask spread and the number of trades are generally higher after news events compared to no-news days, whereas volatility, liquidity and trading activity are weakly affected or unaffected prior to news events except for CR news. Further, order imbalance is lower after earnings news, suggesting more two-sided trading at this time. In the next section, we examine the patterns of sidedness around news events.

IV. The Sidedness of Markets around News Events

We expect trade initiations to be on one side of the market if they are motivated by asymmetric information. If trading is based on differential information or beliefs, we expect trade triggering orders to arrive on both sides of the market. Presumably each of the various motives drives trading to some extent, and we seek evidence of each in the transactions data. To identify news-related trading motives, we estimate sidedness for the first 15 minutes of days around news events. Prior to a scheduled news release, trading may be motivated by differences of opinions regarding the expected content of the news. Thus we compare sidedness before earnings and macro news for large versus small dispersions of analyst forecasts. We expect news associated with a large dispersion to result in markets that are more two-sided. Following a news release, sidedness is likely to be determined by the magnitude of any news surprise and so, after earnings and macro news, we compare reports with large versus small surprises.

We estimate sidedness by the correlation between *ZBUY* and *ZSELL*, as follows:

$$ZBUY = \frac{BUY - Mean(BUY)}{SD(BUY)} \tag{2}$$

$$ZSELL = \frac{SELL - Mean(SELL)}{SD(SELL)} \tag{3}$$

where *BUY* (*SELL*) is the number of buyer (seller) initiated trades in an interval, and Mean and SD are the sample mean and standard deviation. The trading frequency is standardized as it varies by stock. If the correlation between *ZBUY* and *ZSELL* is higher (lower) around news events, compared to the no-news days, then the market is said to be more two-sided (one-sided).

INSERT TABLE III HERE

The results are summarized in the two panels of Table III for the NYSE and Nasdaq stocks separately. In Panel A, we report the mean and median correlation for the no-news days, and for days before and after earnings reports, macro announcements and CR news. The entries ** (*) indicate that the mean and median correlation is significantly different at the 1% (5%) level or less for the before or after sample versus the no-news sample; or for small (SM) versus large (LA) dispersions or surprises. We compare the mean correlations using Fisher's *z*-statistic, and the median correlations using the Wilcoxon *z* statistic.

Because trading in different stocks is likely to be based on a variety of motives (leading to varying degrees of sidedness across stocks), we compare the cross-sectional distributions of the correlation (Panel B of Table III). To do so, we report the *p*-values (*p*+ and *p-)* for the Kolmogorov-Smirnov (KS) one-sided test statistics *D*+ and *D*-, respectively:

$$D+ = \max_j \left(F_1(x_j) - F_2(x_j) \right), \text{ where } j\text{=1,2,...,n.} \tag{4}$$

$$D- = \max_j \left(F_2(x_j) - F_1(x_j) \right), \text{ where } j\text{=1,2,...,n.} \tag{5}$$

x_j is the correlation for the *j*-th stock, *n* is the number of stocks, and F_1 (F_2) is the control (test) sample distribution. The variables *D*+ and *D*- show the maximum vertical distances between the distributions. Thus, a low value for *p*+ (*p*-) indicates that the correlation distribution in the test sample lies significantly below (above) the distribution in the control sample, which indicates relatively greater *one-sidedness* (*two-sidedness*) of the test sample compared to the control sample.[13] The control sample is the no-news or large (LA) dispersions or surprises; the test sample is the before or after sample, or the small (SM) dispersion or surprises.

Results from Table III are discussed in Section IV*A* for earnings reports, in Section IV*B* for macro news in and in Section IV*C* for CR news. We summarize the results in Section IV*D*.

A. Sidedness around Earnings Reports

INSERT FIGURE 1 HERE

Trading is more one-sided prior to earnings news releases. In both markets, the mean correlation is significantly lower for days before earnings reports compared to the no-news sample. Figure 1 plots the correlations for different stocks by percentiles before earnings news and the no-news samples. The top panel shows that the correlation distribution for days before earnings reports generally lies below that for the no-news days in both markets. Consistent with the figures, the KS statistics in Panel B reveal that $p+$ is 0.05 for the NYSE stocks and 0.03 for the Nasdaq stocks, whereas $p-$ exceeds 0.20 in both markets, indicating that the correlation distribution before earnings news is significantly more one-sided but not significantly more two-sided than that before no-news days.

Next, we compare reports with large versus small forecast dispersions. For the NYSE stocks, the median correlation is 32% lower (0.15 versus 0.47) and the mean correlation is 30% lower when the dispersion is small than when it is large, and these differences are statistically significant. The median and mean correlations are also higher for larger analyst dispersions for the Nasdaq stocks, but not with statistical significance. In the bottom panel of Figure 1, we observe that the distribution for large dispersions generally lies above that for small dispersions; and the KS statistics in Panel B show that the difference is significant for both markets. For example, $p+$ is 0.05 for the Nasdaq stocks, indicating that the correlation distribution is significantly more one-sided when the dispersion is smaller. These results show that trading is relatively more two-sided before earnings reports with larger differences of opinions.

INSERT FIGURE 2 HERE

Trading for both NYSE and Nasdaq stocks is more two-sided following earnings reports. This is indicated for the "*After*" sample by the significantly higher median and mean correlations. The top panel of Figure 2 illustrates the relative two-sidedness of the correlation distribution for the "*After*" sample compared to the no-news sample, and the KS statistics show that the difference is significant. Sidedness is not significantly different for NYSE stocks after conditioning on the size of the earnings surprise. But, for the Nasdaq stocks, the mean correlation is 17% smaller for small compared to large surprises, indicating more two-sided trading following large surprises. These results are consistent with Kim and Verrecchia (1994) who show that more diverse information is acquired when the forecast is less precise (i.e. the surprise is larger). The greater diversity of information leads to more two-sided trading.[14]

We examine whether investors' divergent beliefs before earnings news (as indicated by the sidedness measure) converge after the news is released. Brown and Han (1992) find evidence of belief convergence after earnings reports, but Morse, Stephan and Stice (1991) do not. Belief convergence occurs if sidedness *after* the releases is similar for large and small *pre-news* dispersions. Thus, we estimate sidedness in the "*After*" sample after conditioning on the pre-news dispersion. The results, shown in the bottom row of Panel A, indicate that beliefs do not converge for the Nasdaq stocks. Specifically, the median correlation is 19% lower (0.59 versus 0.78), the mean correlation is 20% lower, and the correlation distribution is more one-sided, when the pre-news dispersion is small than when it is large. This result is consistent with Diether, Malloy and Scherbina (2002) who show that stocks with high analyst disagreements continue to under-perform for six months on average. For NYSE stocks, differences in sidedness for large and small pre-news dispersions are not statistically significant after news releases.[15]

B. Sidedness around Macroeconomic Announcements

INSERT FIGURE 3 HERE

Turning to macro news, we find that sidedness is not significantly different before macro reports relative to the no-news sample. As with earnings reports, two-sided trading prior to macro news appears to be driven by divergent opinions. As seen in the bottom panel of Figure 3, the correlation distributions for large dispersions of opinions generally lie above those for small dispersions in both markets, and the difference is significant for Nasdaq stocks (as shown by the KS test statistics). Further, the median and mean correlations are significantly higher after large dispersions for the Nasdaq stocks. For the NYSE stocks, the mean correlation is lower by 6% for smaller dispersions although the difference is not significant. Our results complement that of Beber and Brandt (2006) who use prices of economic derivatives to measure macro uncertainty and find that it is a significant determinant of trader behavior in the financial markets.

INSERT FIGURE 4 HERE

After macro announcements, sidedness is not significantly different from the no-news days. There is weak evidence that trading is more two-sided after large surprises. The mean correlation is significantly lower for small compared to large surprises for Nasdaq stocks. The correlation distribution (as illustrated in the middle panel of Figure 4) appears more two-sided after large surprises, although the difference is not statistically significant. Finally, the bottom row of Panel A shows that belief convergence occurs in both markets, as post-announcement sidedness is statistically similar for small and large dispersions.

C. Sidedness around CR News

INSERT FIGURE 5 HERE

CR news days, unlike earnings and macro reports, are not predictable. Thus, insiders may have private information regarding both the time and the content of the news. Indeed, we find that trading is more one-sided prior to CR news for Nasdaq stocks; the mean correlation is 18% lower before CR news than in no-news days, and the difference is significant at the 5% level. After CR news, trading is more two-sided for the NYSE stocks. The mean correlation is greater than in the no-news sample, and the difference is statistically significant; moreover, the KS statistics indicate significantly more two-sidedness but not significantly more one-sidedness after CR news compared to the no-news sample (also see Figure 5).

D. Overview and Summary

More one-sided trading is observed before earnings or CR news compared to the no-news sample, consistent with pre-news trading motivated by asymmetric information. In contrast, sidedness is unaffected before public macro news. Comparing earnings and macro news with small and large analyst forecast dispersions, we find relatively more two-sided markets prior to news with larger dispersions, which is consistent with trading being driven by differences in opinions. Trading is also generally two-sided following news reports (in particular after large news surprises), consistent with traders expending resources to understand the import of publicly disclosed financial news (Fishman and Hagerty (1989)). The divergent pre-news beliefs of investors are more likely to converge after macro news than after earnings news.

V. Sidedness as a Determinant of Liquidity, Volatility, and Trading Activity

The particular association that volatility, liquidity and trading activity has with sidedness can provide further insights into the underlying motives for trading. For example, high volatility and trading costs may be evidence either of asymmetric information or of dispersed opinions. However, the former results in one-sided markets which accentuate trading costs, while the latter leads to two-sided markets that can mitigate trading costs. Therefore, asymmetric information should lead to increased trading costs for stocks with more one-sided trading. In contrast, dispersed opinions should lead to higher volatility, but lower or similar trading costs, for stocks with more two-sided trading. Accordingly, we sort stocks by the degree of "excess" sidedness, and then consider the relationship with volatility, liquidity, and trading activity. The methodology for estimating "excess" sidedness is described in Section V*A*. Results for earnings reports are given in Section V*B*, for macro announcements in Section V*C*, and for CR news in Section V*D*. A discussion and overview of the results is provided in Section V*E*.

A. Methodology

We determine whether a stock exhibits "excess" *CORR*, relative to a benchmark level. Let $CORR_{iS}$ be the correlation for stock *i* in sample *S*, where S=T (the test sample) or S=N (the control sample). Let the benchmark correlation be $CORR_N$, the median over all stocks of $CORR_{iN}$. Then, a stock *i* in sample *S* is *more two-sided* if:

$$CORR_{iS} \geq CORR_N \tag{6}$$

Alternatively, a stock in sample *S* is *less two-sided* if:

$$CORR_{iS} < CORR_N \tag{7}$$

INSERT TABLE IV HERE

After sorting stocks into two groups *L* (less two-sided) and *M* (more two-sided), we estimate the mean and median differences in *HILO*, *PEBAS*, *NTR* and *AIMB* between them. These statistics, reported in Table IV, are indicated by the label "*L-M*" (less minus more two-sided). Let N_i be the number of 5-minute intervals in group i=*L*, *M*. The table reports *DIFN*=$100(N_L - N_H)/(N_L+N_H)$, which indicates the preponderance of trading intervals that are less two-sided, relative to the no-news days. The table also shows differences in the various statistics between reports with small versus large forecast dispersions (labeled "*SM-LA dis*") or with small versus large news surprises (labeled "*SM-LA sur*"). In these cases, *DIFN* is the relative incidence of trading intervals with smaller dispersions or surprises. A positive number indicates a higher value for less two-sided trading intervals (or for smaller dispersions/surprises).

B. Results for Days around Earnings Reports

Table IV, Panel A presents the results for earnings reports. In the columns labeled "*No news: L-M,*" we show results for the control (i.e. no-news) sample. In both markets, *NTR* is higher and *AIMB* is lower for more two-sided stocks; *PEBAS* is higher for more one-sided stocks, which may reflect the impact of inventory imbalance on liquidity suppliers. The result for *HILO* is inconsistent: it is greater (lower) for the more two-sided Nasdaq (NYSE) stocks.[16]

For days before earnings reports ("*Before: L-M*"), we see that *DIFN* is positive (11% for NYSE and 36% for Nasdaq), showing a higher incidence of more one-sided intervals before earnings news compared to no-news days, as in our earlier results. Also, *NTR* is significantly greater for the more two-sided stocks. These stocks also have higher volatility, but statistically similar or lower spreads, as well as lower imbalance. These results hold for both markets.

We now compare market dynamics for earnings reports with small versus large dispersions ("*Bef: SM- LA dis*"). News reports with large dispersions are associated with higher

HILO and *NTR*, and lower *AIMB*, but similar *PEBAS*, vis-à-vis reports with small dispersions. These results hold in both markets. Thus, market dynamics are similar for more two-sided stocks and for larger forecast dispersions, supporting the view that differences of opinion drive two-sided trading prior to earnings reports.

For both NYSE and Nasdaq stocks, *DIFN* is substantially negative for days after earnings reports ("*After: L-M*"), consistent with our earlier findings that predominantly two-sided trading follows earnings news. In the Nasdaq sample, the more two-sided stocks have greater *NTR* and volatility along with lower spreads and imbalance. For the NYSE stocks, market dynamics for the more two-sided stocks are statistically similar to those for the less two-sided stocks.

Conditioning on the size of the surprises ("*Aft: SM- LA sur*"), we find that *NTR* is higher, while *PEBAS* and *AIMB* are lower for Nasdaq stocks when the surprise is larger. The similarity of market dynamics for more two-sided Nasdaq stocks and for larger surprises supports the idea that two-sided trading after earnings news with large surprises is driven by differentially informed traders. While more informative trading leads to higher bid-ask spreads after earnings news for all stocks, spreads increase relatively less for more two-sided stocks. For the NYSE stocks, differences in market quality between small and large surprises are not significant, just as differences in sidedness between small and large surprises are also not significant. These results, therefore, suggest that the sidedness measure may predict market quality following news events.

We have seen evidence of continued belief divergence after earnings news, as indicated by the sidedness measure. Does belief divergence also result in divergence in market dynamics? We examine market dynamics after news for small and large pre-news dispersions. The results, shown in the columns labeled "*Aft: SM-LA dis*," indicate that, following earnings news releases, *HILO* and *NTR* remain significantly higher in both markets, and that the median *PEBAS* is significantly greater in the NYSE market for reports with larger pre-news dispersions. Thus, differences in sidedness and market dynamics between reports with large and small pre-news dispersions persist following earnings news releases, consistent with belief divergence.

C. Results for Days around Macro Announcements

In both markets, for days before macro announcements (Table IV, Panel B), the more two-sided stocks are characterized by greater volatility and number of trades, and lower spreads and imbalances, as shown in the columns labeled "*Before: L-M*." After sorting the macro reports by analyst forecast dispersions ("*Bef: SM- LA dis*"), we find for Nasdaq stocks that volatility is higher when dispersions are small but the other statistics do not differ significantly between the small and large dispersions. Thus, while sidedness is related to market dynamics before macro news, forecast dispersions are (mostly) not. This may be because the sidedness measure is stock-specific whereas, by construction, the macro dispersion measure pertains to *all* stocks having either one-sided or two-sided markets on a particular macro news day.[17] If stocks have different sensitivities to macro risk, then the stock-specific sidedness measure is expected to be more informative than the market wide dispersion measure.

Following macro announcements ("*After: L-M*"), volatility and *NTR* are higher, and spreads and imbalance are lower for more two-sided stocks in both markets. In the columns labeled "*Aft: SM- LA sur*" we observe few statistically significant differences in volatility, liquidity or trades for large and small surprises. As with the macro dispersion measure, the macro surprise measure may not be highly informative of stock-level dynamics because it pertains to *all* stocks on days with large surprises.

Our evidence, as based on sidedness, has thus far pointed to belief convergence after macro news. In the columns labeled "*Aft: SM-LA dis*," we see that the market dynamics for

NYSE and Nasdaq stocks are (with one exception) statistically similar after macro news for reports that are sorted based on the size of pre-news forecast dispersions. Thus, both sidedness and market dynamics converge following macro news, consistent with convergence in beliefs.

D. Results for Days around CR News

Trading prior to CR news is strongly one-sided for the NYSE stocks, as shown by the large and positive value of *DIFN* (51%) in the column labeled "*Before: L-M.*" For the Nasdaq sample, the more one-sided stocks have higher spreads and imbalance, but are less active and have lower volatility. There is a greater incidence of two-sided intervals following CR news, as is shown by the large, negative values of *DIFN* (-81% for NYSE and -40% for Nasdaq). The more two-sided stocks have greater volatility and more trades in both markets.

E. Overview and Discussion

Combining sidedness and market dynamics sheds further light on trade initiations. We find higher volatility and number of trades, lower order imbalance, and mostly similar (in a statistical sense) effective spreads, before earnings news when trading is more two-sided *and* when analyst forecast dispersions are large.[18] These results are consistent with differences of opinions driving trading before news releases. We also find that two-sided trading after news with a large surprise element appears to be driven by differentially informed traders. As corroborating evidence, greater volatility and trading, along with lower order imbalance, prevail after earnings news when trading is more two-sided *and* when the surprises are large. These results suggest (but do not directly show) that dispersions and surprises may impact the market via sidedness; the simultaneous equations analysis in the next section will address this issue.

When pre-news beliefs converge (diverge) after news releases, as indicated by convergence (divergence) in sidedness, differences in market dynamics between small and large pre-news dispersions are insignificant (significant) after these events. Thus, sidedness is another measure of belief divergence, complimenting measures of analyst forecast dispersions.

We find higher bid-ask spreads and imbalance prior to CR news when trading is relatively more one-sided, consistent with news-driven trades. However, more one-sided stocks are also less volatile, which is inconsistent with the asymmetric information motive. The result may be explained by heterogeneous beliefs generating stronger volatility for the more two-sided stocks, with this latter effect dominating the news-driven volatility for the more one-sided stocks. Allowing for the co-determination of sidedness and volatility may lead to more consistent results. We turn to this issue in the next section.

VI. Simultaneous Determination of Sidedness, Liquidity, Volatility, Number of Trades and the Order Imbalance

While we have shown that sidedness determines market dynamics, causality may also go in the opposite direction. For instance, two-sidedness may be explained by a temporary decrease in the bid-ask spread. We examine in Section VI*A* a scenario where the bid-ask spread or order arrivals are exogenous, and then consider the impact on sidedness. In section VI*B*, we estimate sidedness, liquidity, volatility and trading activity in a simultaneous equations framework to assess the extent to which these variables are co-determined. We have shown that more two-sided stocks generally (but not always) have lower imbalance, suggesting that they may reflect complementary types of information.[19] In Section VI*C*, we examine how sidedness and order imbalance are related by including imbalance in the simultaneous equations system.

A. Sorting Stocks by the Bid-Ask Spread and the Number of Trades

A temporary decrease in the bid-ask spread may occur, perhaps due to an exogenous increase in limit order arrivals, thus reducing the cost of immediacy. Then, more traders are apt to submit market orders, as further price improvements are less likely (Parlour (1998); Foucault (1999); Foucault, Kadan and Kandel (2005)). Trading will be two-sided if the market orders are submitted on both sides of the market. Liquidity is higher (lower trading costs are the original impetus for trades), but the effect on volatility is ambiguous: while a smaller bid-ask bounce leads to lower volatility, the increased demand for liquidity could increase higher volatility.

To examine this scenario, we sort stocks by the "excess" bid-ask spread using the methodology described in Section V*A* (these results are not reported here). Let $PEBAS_{iT}$ be the mean effective spread for stock *i* in the test sample *T* and $PEBAS_N$ be the median spread over all stocks in the control sample *N*. A stock in sample *T* is in the "high spread" group if $PEBAS_{iT} \geq PEBAS_N$; otherwise the stock is in the "low spread" group. We then calculate differences in *CORR*, *HILO*, *NTR*, and *AIMB* between the "high spread" and "low spread" groups.

Since our interest is in scenarios where the bid-ask spread has decreased, we identify events with an unusually high number of stock-intervals in the "low spread" group. We find that these events mostly occur in the Nasdaq market following earnings and CR news, and before and after macro news. For these events, stocks in the "low spread" group are more two-sided (i.e. with higher *CORR* and lower *AIMB*), and have substantially greater trading and lower volatility, compared to stocks in the "high spread" group. These results are consistent with lower spreads leading to more two-sided markets. Sidedness and *NTR* are not statistically different for NYSE stocks with unusually low and unusually high spreads.

Since an exogenous increase in order arrivals may cause the spread reduction, we further consider the effect on market dynamics after sorting stocks into "high *NTR*" and "low *NTR*" groups.[20] We focus on events with an unusually high incidence of stock-intervals in the "high *NTR*" group. The identified events for Nasdaq stocks are after earnings reports, before macro news, and before and after CR news; and after earnings news for NYSE stocks. For these events, the more heavily traded stocks are more two-sided, and have lower spreads and higher volatility.

We conclude that a temporary decrease in the bid-ask spread is a likely source of trade initiation. Reduced spreads and increased order arrivals result in more two-sided markets, suggesting that sidedness, spreads and order arrivals are simultaneously determined.

B. Simultaneous Equation Results

In the previous section, we saw that sidedness is an outcome of changes in spreads and order arrivals. The arrival of market orders is also likely to be endogenous, depending on expected volatility and spreads; in turn, volatility and the spread may depend on the expected order arrivals. Moreover, we have shown that volatility, spreads and order arrivals are determined by the expected sidedness of the market. To account for the co-determination of these variables, we estimate a simultaneous equation system with sidedness, liquidity, volatility and the number of trades as endogenous variables. We use the two-stage least squares (2SLS) method to obtain consistent estimates.[21] In the first-stage, we regress *CORR*, *PEBAS*, *HILO* and *NTR* on these instrumental variables (IV): *L1CORR*, *L1PEBAS*, *L1HILO*, *L1NTR*, where *L1X* is the first lag of X. For earnings and macro news, we also include the dummy variable *DIS*/*SUR* which equals one for the largest 50% of values of analyst forecast dispersions (news surprises) in the *before* (*after*) sample, and is zero otherwise. An observation is a 5-minute interval *i* for stock *j* on day *t*. *CORR* is estimated over all days of stock *j* for an interval *i*. As before, only the first 15 minutes of each day is used in the analysis.

Let *E(CORR)*, *E(PEBAS)*, *E(HILO)* and *E(NTR)* denote the fitted values from the first-stage regression. The second stage regressions for interval *i*, stock *j* and day *t* are:

$$CORR_{ijt} = a_0 L1CORR_{ijt} + a_1 E(PEBAS)_{ijt} + a_2 E(HILO)_{ijt} + a_3 E(NTR)_{ijt} + e1_{ijt} \quad (8)$$

$$PEBAS_{ijt} = b_0 L1PEBAS_{ijt} + b_1 E(CORR)_{ijt} + b_2 E(HILO)_{ijt} + b_3 E(NTR)_{ijt} + e2_{ijt} \quad (9)$$

$$HILO_{ijt} = c_0 L1HILO_{ijt} + c_1 E(CORR)_{ijt} + c_2 E(PEBAS)_{ijt} + c_3 E(NTR)_{ijt} + e3_{ijt} \quad (10)$$

$$NTR_{ijt} = d_0 L1NTR_{ijt} + d_1 E(CORR)_{ijt} + d_2 E(PEBAS)_{ijt} + d_3 E(HILO)_{ijt} + e4_{ijt} \quad (11)$$

where *e1* to *e4* are the error terms. In each equation, we include the first lag of the left-hand side variable and exclude the three remaining pre-determined variables; thus the system of equations (8)-(11) is exactly identified. For earnings and macro news, we also include *DIS*/*SUR* as a pre-determined variable in the second stage regressions.

A practical issue in estimating the regressions is the availability of enough observations to obtain reliable statistical results, in particular for the CR and earnings news samples. For this reason, we pool the NYSE and Nasdaq stocks for CR news. For the earnings news, there are important differences in results between markets, and so we pool the earnings and macro news for each market.[22] For the no-news sample, results are similar for the two markets and we pool the NYSE and Nasdaq stocks in order to avoid repetition.

INSERT TABLE V HERE

Theory suggests that *CORR* and *NTR* should each be autocorrelated. For example, Parlour (1998) and Foucault (1999) imply a clustering of two-sided liquidity trades: periods of two-sided markets with high liquidity are apt to trigger further market orders on both sides of the market. In Table V, we present first order autocorrelation statistics for *HILO*, *PEBAS*, *CORR* and *NTR* on no-news days and around news events. All autocorrelations are significantly different from zero at the 1% level or less. Consistent with theory, *NTR* has a high degree of positive autocorrelation (exceeding 0.70 in all samples); *CORR* is also highly autocorrelated, especially for Nasdaq stocks, comparable in magnitude to the autocorrelation of *HILO* and *PEBAS*. *HILO* and *PEBAS* are positively autocorrelated, as in prior research.

We further observe in Table V that the autocorrelation in *CORR* switches from 0.54 in the no-news sample to -0.22 in the days before CR news. The result is consistent with the possibility that, in advance of a private information event, insiders with long-lived information submit limit orders (Kaniel and Liu (2006)) while they submit market orders closer to the event, implying a switch from two-sidedness to one-sidedness.[23]

INSERT TABLE VI HERE

Results from the simultaneous regressions are presented in Table VI (pre- and post-event results are given in Panels A and B, respectively). For the first-stage regressions, we only present results involving *LICORR* for the sake of brevity. From Panel A, we find in the first-stage regressions that a higher *L1CORR* is a positive and significant determinant of *HILO* and *NTR* in seven of eight samples---i.e. more two-sided markets appears to predict higher volatility and more trading. In addition, *LICORR* is a negative and significant determinant of *PEBAS* in one sample (and significant at a 10% level in another sample), suggesting that more two-sidedness may predict lower effective spreads.

In the second stage regressions, there is evidence of co-determination of sidedness, volatility, trades and spreads for no-news days. Higher *E(HILO)* and *E(NTR)*, and lower *E(PEBAS)* are associated with more two-sided markets. In turn, when markets are expected to be more two-sided (i.e. *E(CORR)* is higher), *NTR* and *HILO* are greater; also, *PEBAS* is lower, although this result only holds at the 10% level of significance. Next, consider results for before CR news. Evidence of co-determination is weaker, likely due to the small number of observations. Unlike the other samples, we observe that *E(CORR)* and *HILO* are negatively related, consistent with trades that are motivated by asymmetric information resulting in more one-sided markets and boosting volatility prior to CR news.[24]

In the second-stage results for days before earnings and macro news, greater forecast dispersion increases *CORR* in both markets, reaffirming the close association between belief heterogeneity and two-sidedness. Increased dispersion leads to lower volatility and *NTR* in the Nasdaq markets; this is in addition to the indirect effect of dispersion on these variables via its impact on sidedness. There is also evidence of co-determination of all variables for the Nasdaq stocks. *E(HILO)* and *E(NTR)* are positive determinants, while *E(PEBAS)* is a negative determinant, of *CORR*; in turn, *E(CORR)* is positively associated with *HILO* and *NTR*, and negatively associated with *PEBAS*. For the NYSE stocks, sidedness and *NTR* are co-determined; also *E(CORR)* is a significant determinant of *HILO*, but the reverse is not true.

For post-news events (Panel B), the first stage regressions reaffirm that *LICORR* may predict *HILO*, *NTR* and *PEBAS*. In the second stage regressions, an important result is that in the CR sample, *E(CORR)* is positively associated with *HILO*, whereas the association is negative in the pre-news sample. In other words, more two-sided stock-intervals are more volatile, consistent with investors acquiring diverse information to interpret CR news. As in the pre-news sample, all variables are co-determined for Nasdaq stocks (except that *E(CORR)* is not significantly related to *NTR*). Also, trading is more two-sided on days with large news surprises in both markets, suggesting that the incentive to acquire diverse information is greater when the surprise is larger. Controlling for sidedness, volatility and *NTR* are generally lower and spreads are generally higher on days with large surprises. Thus, news surprises impact the market both directly and indirectly via the sidedness measure.

The simultaneous equation results show that sidedness, spreads, order arrivals and volatility are co-determined in various scenarios: no-news days, and around earnings and macro news for Nasdaq stocks. The results reaffirm the link between sidedness, forecast dispersions and news surprises; and, more generally, between sidedness and sources of trade initiation. Finally, sidedness appears to have predictive power for order arrivals, volatility and spreads.

C. Sidedness and the Order Imbalance

Similar to sidedness, order imbalance may also be used for identifying trading motives.[25] To clarify the relation between imbalance and sidedness, we include order imbalance (*AIMB*) and its lagged value (*L1AIMB*) in the simultaneous equations. (These results are not reported here). We find that increased dispersion or surprise predicts more two-sided markets in all cases, but is not significantly related to imbalance. This shows that, unlike sidedness, imbalance is not an indicator of belief heterogeneity or differential information. In all samples, *L1CORR* is a significant, negative indicator of *AIMB*: increased two-sidedness predicts lower imbalance. Reciprocally, *L1AIMB* is also a significant predictor of *CORR* in three of five samples. Thus, sidedness and imbalance are informative of each other. Moreover, both *LICORR* and *L1AIMB* are generally significant predictors of volatility and *NTR*, demonstrating that each is informative of market dynamics in the presence of the other. We conclude that sidedness and imbalance are jointly informative of each other and of market dynamics. However, belief heterogeneity is reflected in sidedness and not in imbalance.

VII. Results for Opening and Closing Minutes of Days without News

Trades may be initiated because of an aggregate shock to traders' impatience, resulting in increased two-sidedness if impatient participants arrive as both buyers and sellers. Traders are likely to be less impatient after a call auction (Bosetti, Kandel and Rindi (2006)). Since the NYSE had an opening call during our sample period but Nasdaq did not, we examine the first 5 minutes of trading in both markets. We also examine the last 5 minutes of trading when traders are likely to become more impatient (Tkatch and Kandel (2006)). As discussed in Foucault, Kadan and Kandel (2005), comparing market dynamics in the closing period of the day with an earlier intra-day interval is similar to analyzing the proportion of impatient traders in their model. Since news arrivals complicate the identification of effects attributable to impatience shocks, we compare sidedness and market dynamics for the first and last 5 minutes to the middle periods (i.e. from 12PM to 3PM) of *no-news* days, referred to as "*Mid-day*." We also examine the last 5 minutes of days when the bid-ask spread has increased between 12PM and 3PM since traders may be more likely to wait till the end of the day to execute orders in this situation.[26]

INSERT TABLE VII HERE

Results for the first 5 minutes of no-news days are in Table VII. Panel A gives descriptive statistics for the first 5 minutes and for the average of the middle periods. Volatility and *PEBAS* are higher, and *AIMB* is lower, compared to the mid-day intervals. Consistent with increased two-sidedness, *CORR* increases in both markets. For Nasdaq stocks *NTR* is substantially higher, indicating a high demand for immediacy. In contrast, for NYSE stocks, the median *NTR* is lower and the mean *NTR* is little-changed, compared to the mid-day period.

To examine whether sidedness is a determinant of market dynamics in the first 5 minutes, we sort stocks by their "excess" sidedness relative to the mid-day period, as in Section V*A*. The results are reported in Panel B. We find that DIFN is large and negative, indicating more two-sided intervals in the first 5 minutes relative to the mid-day. For the Nasdaq stocks, the more two-sided stocks have higher *NTR* and volatility. In contrast, for the NYSE sample, the more one-sided stocks have higher *NTR* and volatility. These results are consistent with increased impatience of Nasdaq traders, relative to NYSE traders, in the first 5 minutes: impatient buyers and sellers on Nasdaq place orders on both sides of the market and drive up volatility.

To obtain lag values, we expand the opening period to 15 minutes and divide it into three 5-minute intervals. We divide the "*Mid-day*" sample (12PM to 3PM) into three hourly intervals. The autocorrelation of sidedness (Panel C) indicates that it is highly persistent, especially for Nasdaq stocks. Select second-stage regression results from the simultaneous equations are shown in Panel D. We find, for both markets, that *E(CORR)* is a positive determinant of *NTR* and, conversely, that *E(NTR)* is positively associated with *CORR*. In addition, for the Nasdaq stocks, *E(CORR)* is a positive determinant of *HILO* and a negative determinant of *PEBAS*. Conversely, higher *E(HILO)* and lower *E(PEBAS)* are significantly associated with higher values of *CORR*. In contrast, for the NYSE stocks, *E(CORR)* is unrelated to *NTR* and *PEBAS*. The persistence of two-sidedness and its significant association with market dynamics are further evidence of the high immediacy demand for Nasdaq stocks in the opening minutes.

INSERT TABLE VIII HERE

Results for the last 5 minutes of days without news are presented in Table VIII. Panel A shows descriptive statistics for the last 5 minutes and for the average of the middle periods. Volatility, *PEBAS* and *NTR* are all higher, and the absolute imbalance is lower, compared to the mid-day intervals. Trading in the last 5 minutes, compared to the mid-day intervals, is less two-sided for the NYSE stocks but more two-sided for the Nasdaq stocks, as shown by the median and mean correlations. When the bid-ask is increasing ("*Last 5 min, inc spd*") for the NYSE stocks, there is greater two-sided trading and higher *HILO* compared to the entire last 5-minute sample, which is consistent with a bigger shock to impatience on these days.

We sort stocks by their "excess" sidedness relative to the mid-day period (Panel B). For Nasdaq stocks, *DIFN* is -40% indicating more two-sided intervals in the last 5 minutes relative to the mid-day period; also, *NTR* and volatility are higher, and the spread lower, for these more two-sided stocks. The results are consistent with impatient buyers and sellers placing orders on both sides of the market in the last 5 minutes. Recall that, for stocks in aggregate, the bid-ask spread is higher in the last 5-minutes compared to the mid-day period; these spread increases are tempered for stocks with more two-sided trading. Trading is more one-sided for NYSE stocks (*DIFN* is 30%). Further, the more one-sided stocks are more active and have greater volatility. However, on days with increasing spreads, there are relatively more two-sided trading intervals (*DIFN* is -13%), and the more two-sided stocks have volatilities that are statistically similar to their mid-day values. This suggests relatively more impatience-driven trades in the closing minutes when the spread is trending up in the NYSE.

Next, we expand the sample to the last 15 minutes of the day to obtain lag values. The autocorrelation statistics (Panel C) reveal moderate persistence in sidedness. Second-stage regression results (Panel D) show that for the Nasdaq stocks, *E(CORR)* is a positive and significant determinant of *HILO* and *NTR*; conversely, higher *E(HILO)* and *E(NTR)*, and lower *E(PEBAS)*, are generally associated with greater *CORR*, consistent with a greater demand for immediacy resulting in more two-sided markets. For the NYSE stocks, higher *E(CORR)* is related to lower *HILO* and *NTR*; and higher *E(HILO)* indicates lower *CORR*. These results imply that greater volatility in the closing minutes is associated with more one-sided trading on the NYSE but more two-sided trading on the Nasdaq, as we have found.

Overall, the results are consistent with impatience being a driving motive for trading in the opening and closing minutes of days without news, especially in the Nasdaq market.

VIII. Additional Investigations

We check the robustness of our findings by assessing (in Section VIII*A*) the accuracy of the Lee-Ready (1991) algorithm for determining trade direction. We do so by deleting particular trades (e.g. those at the mid-quote) that are more likely to be classified inaccurately. In Section VIII*B*, we use the absolute volume imbalance as an alternative measure of sidedness so as to capture the effects of large trades that are more likely to be executed by institutional investors. Better informed institutions (e.g. portfolio managers of value funds) may be more impatient and have more one directional order flow than retail customers. Other institutions may be impatient and trade rapidly on both sides of the market (e.g. hedge funds seeking to exploit short-run trading opportunities). Alternatively, institutions such as index funds, looking only to passively mimic an index, may be more patient than retail traders. Thus, whether institutions have a greater or a lesser demand for immediacy than retail traders is an empirical question.

A. The Effects of Errors in Classifying the Trade Direction

Ellis, Michaely and O'Hara (2000) show for Nasdaq stocks and Peterson and Sirri (2003) find for NYSE stocks that the Lee-Ready (1991) algorithm is accurate between 81% and 93% of the time. However, the algorithm is less accurate for trades that are inside the quotes and for trades at the mid-quote. Thus, we repeat our analysis after deleting these trades. In our sample, 10% and 8% of NYSE and Nasdaq trades, respectively, occur at the mid-quote, while 27% and 36% of NYSE and Nasdaq trades, respectively, occur inside quotes but not at the mid-quote.

With these trades deleted, all of our results continue to hold, and in some cases become stronger. For example, the results are stronger before CR news, when trading is more one-sided. Whereas earlier, this result was significant only for Nasdaq stocks, we now obtain statistically significant results for both markets. Consistent with earlier results, we find that, for the first 5 minutes of the day, trading is more two-sided compared to the mid-day in both markets. Further, trading is more one-sided before earnings news and more two-sided after all news; the more two-sided stocks are typically more volatile and trade more, but have lower spreads and imbalance.

B. Volume Imbalance

An alternative measure of sidedness is the absolute volume imbalance *VIMB*=|*BVOL*-*SVOL*|/*TVOL*, where *BVOL* (*SVOL*) is the volume of trades initiated by buyers (sellers) and *TVOL*=*BVOL*+*SVOL*. Institutional orders are generally larger than retail orders. Thus, if institutional trades are mostly on one side of the market, we will observe a high value of *VIMB*, even when trading is two-sided according to the sidedness measure based on the number of trades *NTR*. Conversely, a low value of *VIMB* may indicate two-sided trading by institutions.

INSERT TABLE IX HERE

Results using *VIMB* are reported in Table IX. Panel A reports the mean and median of *VIMB* for the first and last 5 minutes of days without news. We find *VIMB* is significantly lower at these times, compared to the mid-day periods, indicating more two-sided trading. Earlier, we had reported one-sided trading in NYSE stocks in the last 5 minutes when using the *NTR*-based measure. The new evidence of two-sidedness suggests that institutions, when trading on the NYSE, are more impatient in the closing minutes compared to retail traders, perhaps because institutions such as index mutual funds need to trade at the closing price for tracking purposes.

Panel B reports the statistics for *VIMB* around news events. Before earnings and CR news, a significantly higher median *VIMB* for NYSE stocks indicates more one-sided trading. In both markets, *VIMB* is lower before earnings reports with larger forecast dispersions, and after larger news surprises, indicating more two-sided trading when differences of opinions and information are greater. These findings are consistent with our prior results. There are however some differences with earlier results such as higher *VIMB* before macro news and after CR news for NYSE stocks which, in contrast to the correlation-based measure of sidedness, indicates greater one-sided markets. In addition, we show in Panel C that *DISPERSION* and *SURPRISE* are not significantly associated with *VIMB* in the simultaneous equations.

We conclude that the results are generally robust to the use of *VIMB* as a sidedness measure. However, *VIMB* is not significantly associated with proxies for belief heterogeneity once we allow for the co-determination of *VIMB* and market dynamics.

IX. Conclusion

We have sought to gain further insight into the drivers of trade initiation: superior information, differential information and/or beliefs, and exogenous changes in the demand for or price of immediacy. To this end, we examine patterns of buyer-initiated and seller-initiated trades in five-minute time intervals around news events (e.g. earnings news) and liquidity events (i.e. the opening and closing minutes of days without news). Of primary importance is the correlation between buy-side and sell-side trade initiations; an increased (decreased) correlation indicates that trading is more two-sided (one-sided). By assessing the association of sidedness with market dynamics (e.g., volatility, liquidity, the number of trades and the order imbalance) in the context of the various events, we draw inferences concerning the motives for trade initiation.

Using a matched sample of 41 NYSE and 41 Nasdaq stocks for the period January 2003 to May 2003, we detect evidence that trades are initiated for each of the motives that we have considered. Trading appears to be driven by asymmetric information prior to merger news; these trades tend to be one-sided, and they are associated with high trading costs. Also of interest is the evidence that trade initiations are motivated by differential information and/or beliefs. Namely, we observe two-sided trade initiation co-existing with relatively high volatility and trading activity but unchanged trading costs preceding news events when the dispersion of analyst forecasts is high, and following news events when announcement surprises are large. We also observe liquidity-related trading manifested in more two-sided trading with high volatility and trading near market openings and closings. The evidence is strongest for the Nasdaq dealer market, where the demand for immediacy is expected to be greater---in particular, for the opening period when (in contrast to the NYSE) there was no opening call during our sample period. The results are robust to errors in classifying trade direction, and to different trade sizes.

Simultaneous equation regression estimates show that sidedness, the bid-ask spread, volatility, the number of trades and the order imbalance are co-determined. We find that belief heterogeneity is reflected in sidedness rather than in the order or volume imbalance. But, sidedness and imbalance are informative of each other and of volatility and the number of trades.

The analysis demonstrates the utility of sidedness as an analytical tool. Stocks with higher analyst forecast dispersions are more two-sided, which suggests that the sidedness measure is a proxy for disagreements. Convergence (or dispersion) in sidedness is indicative of convergence (or dispersion) in beliefs. Further, increased two-sidedness appears to predict more volatility and trades, and lower bid-ask spreads, even after controlling for the imbalance.

We understand these findings in terms of the richness of the motives for trade initiation that they imply. The sidedness of a market also has important implications for liquidity creation, for the ability of buy-side participants to supply liquidity to each other, and for public policy (e.g., understanding price dynamics during periods of heightened market instability, when trading is likely to be one-sided). We suggest that more attention be given to this variable.

Footnotes

[1] Prior investigations have related order imbalance to liquidity, volatility, and trading costs. Hall and Hautsch (2004) find that the instantaneous buy-sell imbalance is a significant predictor of returns and volatility. Chordia, Roll and Subrahmanyam (2002) show that daily order imbalances are negatively correlated with liquidity.

[2] We thank the referee for clarifying the discussion in this section.

[3] For example, a bad news signal leads to a sequence of sell orders as long as the information is only partially revealed in the price, and assuming that informed traders will generally place market orders. If, instead, most insiders place aggressive limit sell orders on receiving a bad signal, then a sequence of buyer-initiated trades may ensue as market orders from the opposite side hit the limit orders; again, a one-sided market results. In Section VI*B* and footnote 23, we discuss the implications of informed traders using both market orders and limit orders.

[4] A one-sided order flow would not obtain in models where price changes follow a martingale (e.g. Kyle (1985)) since if the price change is proportional to order flow (with a fixed constant of proportionality), then order flow must also be a martingale. We thank Joel Hasbrouck for pointing this out to us.

[5] With complete markets, the no-trade theorem applies. With incomplete markets, volume may be low (Wang (1994)).

[6] He and Wang (1995) provide an example (footnote 18 in their paper) of two-sided trading due purely to differential information: half of the investors in the example estimate that the supply shock has increased and buy the stock, while the other half estimate that the supply shock has decreased and sell the stock. Models with dispersed beliefs include Kandel and Pearson (1995), where agents use different likelihood functions to interpret public news. Trading can be two-sided if some agents interpret the public signal more optimistically while others are more pessimistic. Harris and Raviv (1993) develop a model of divergent interpretations where two groups of traders agree whether a signal is positive or negative, but one is more “responsive” to the information. When the cumulative signal is positive (negative), the more responsive (unresponsive) group buys all available shares. As the cumulative signal changes sign, the direction of trades also changes.

[7] The impatience shock could also come from an increase in the cost of delayed execution. In this case also, the volatility and bid-ask spread is likely to increase, but there is no implication for sidedness.

[8] We started with 50 NYSE stocks but had to drop 9 NYSE stocks mostly as they were acquired by or merged with another company. To match based on market value and closing price, we randomly select 41 NYSE stocks that were trading on the last trading day of December 2002, and then select 41 Nasdaq stocks with a market value and closing price that, in combination, were nearest to those of the NYSE stocks on that date. Specifically, for the j^{th} matching variable, let x_j be the data for NYSE stock x, and y_j be the data for Nasdaq firm y, where j=1 (the market value), or 2 (the closing price). The Euclidean distance between NYSE firm x and Nasdaq firm y is:

$$d(x,y) = \sqrt{\sum_{j=1}^{2}(x_j - y_j)^2} \qquad (1)$$

We select a matched Nasdaq firm y to minimize $d(x,y)$. Since variables with large variance tend to have more effect on $d(x,y)$ than those with small variance, we standardize the variables before the minimization.

[9] This filter may effectively smooth the limit order book, potentially boosting a finding for two-sidedness. However, the number of observations affected by the filter is small (about 1.5% of observations for NYSE stocks and about 0.1% for Nasdaq stocks). We have verified that inclusion of the filter does not affect our results qualitatively.

[10] The Lee-Ready (1991) algorithm cannot classify some trades, in particular those executed at the opening auction of the NYSE, and these are omitted from our sample.

[11] For earnings news, our definition of forecast dispersion is consistent with Diether, Malloy and Scherbina (2002). For macro news, we use the median forecast as we do not have data on the mean forecast.

[12] We find that volatility, the bid-ask spread, the number of trades and volume are significantly higher on high return days for both markets, consistent with the idea that the high returns are outcomes of news events. In Easley et al. (2005), the probability that an information event occurs on a particular day is between 0.33 and 0.58 for actively traded stocks. Thus, the 30 percentile cut-off is on the low side of this range, but appears reasonable since we have both active and inactive stocks in our sample.

[13] For a discussion of the KS statistics, see Chakravarti, Laha and Roy (1967).

[14] Since the size of the surprise may be a proxy for how much information is known ahead of time, we partition earnings reports ex-ante based on the size of the surprise ex-post. However, the results (not reported here) reveal no significant differences in sidedness between the partitioned events.

[15] We also find (results not reported here) that beliefs are more likely to converge when the size of the surprise is small than when it is large.

[16]Differences in market structure may account for this result. The demand for immediacy is likely to be highest for dealer markets such as the Nasdaq (Tkatch and Kandel (2006)); thus, immediacy demands of buyers and sellers are more likely to lead to two-sided markets along with high volatility on Nasdaq as compared to the NYSE.

[17] The sidedness and dispersion measures do not correspond perfectly even for earnings news. This is because there is a unique correlation measure (i.e. sidedness) for each stock, whereas there are multiple earnings announcements for a stock, some of which are associated with high dispersion while others with low dispersion.

[18] Frankel and Froot (1990) also find a positive association between dispersion and price volatility.

[19] Sidedness is based on the distributions of buyer- and seller-initiated trades, whereas order imbalance is a summary measure of these distributions (i.e. the difference between the numbers of buy- and sell-triggered trades).

[20] Let NTR_{iT} be the mean number of trades for stock *i* in the test sample *T* and NTR_N be the median number of trades over all stocks in the control sample *N*. We assign a stock in sample *T* to the "high *NTR*" group if $NTR_{iT} \geq NTR_N$; otherwise we assign the stock to the "low *NTR*" group. Then, we calculate the differences in *CORR*, *HILO*, *PEBAS*, and *AIMB* between the two groups.

[21] To account for cross correlation in the regression residuals, we have also estimated the system using a Full Information Maximum Likelihood (FIML) method, but our results remain qualitatively similar.

[22] We have verified that the results also obtain for the macro news sample considered separately.

[23] To further examine this issue, we estimate *CORR* for each 5-minute interval on the day of the CR events and find evidence consistent with a switch in sidedness. For example, in the Nasdaq market, *CORR* is 0.50 or higher for the first 10 minutes of the day, drops to 0.10 in the next 5-minute interval, then increases to 0.72 and stays at a high level for the next 40 minutes.

[24] While we had earlier found a positive relation between sidedness and *HILO* before CR news for Nasdaq stocks, unlike the present case, sidedness was held exogenous in that analysis.

[25] For example, in Easley et al. (2005), the absolute imbalance is taken to reflect asymmetrically informed trade arrivals.

[26] We thank Duane Seppi for suggesting this possibility.

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Figure Captions

Figure 1: Correlation Distribution before Earnings Reports

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days before earnings reports, and separately for reports with small and large divergences of analyst opinions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

Figure 2: Correlation Distribution after Earnings Reports

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days after earnings reports. The figure also plots the correlation distribution for reports with small and large earnings news surprises, and for small and large pre-news analyst forecast dispersions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

Figure 3: Correlation Distribution before Macroeconomic Announcements

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days before macro announcements, separately for reports with small and large divergences of analyst opinions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

Figure 4: Correlation Distribution after Macroeconomic Announcements

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days after macroeconomic announcements. It also plots the correlation distribution for reports with small and large macro news surprises, and for small and large pre-news analyst forecast dispersions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

Figure 5: Correlation Distribution before and after CR News

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days before and after corporate restructuring (CR) news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

Table I: Sources of Trade Initiation: Predictions and Identifying Events

The table presents predictions from models of trade initiation for sidedness, price volatility, trading costs, the number of trades and order imbalance. The sources of trade initiation are: asymmetric information, different information and/or different beliefs, and aggregate shocks to traders' impatience. The table also lists events that are likely to identify the various sources of trade initiation.

Trade initiated due to:	Identifying events	Predictions for:				
		Sidedness	*Price volatility*	*Trading costs*	*Number of trades*	*Order imbalance*
Asymmetric information	Before private news releases	One-sided	High	High	Ambiguous	High
Differences in opinions or differential information	Before scheduled news reports with high analyst forecast dispersion or after scheduled news with large news surprise	Two-sided	High	Ambiguous	High	Low
Increased proportion of impatient traders	Opening session when there is no opening auction; Towards the end of the trading day	Two-sided	High	High	High	Low

Table II: Descriptive Statistics around News Events

The table shows the means and medians of volatility, liquidity, number of trades and the order imbalance around news events. The trading day is divided into intervals of 5-minute duration. The variable *HILO* is ratio of the highest to the lowest price in the interval, minus 1; *NTR* is total number of trades; *AIMB*, or the absolute order imbalance, is the absolute value of (*BUY-SELL*)/*NTR*, where *BUY* (*SELL*) is the number of buyer (seller) initiated trades; *PEBAS* is the average proportional effective bid-ask half-spread in an interval, defined as *Q**(*P- M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. Estimates for *HILO*, *PEBAS* and *AIMB* are multiplied by 100. Statistics are shown for the first 15 minutes of days before and after news events: earnings reports, macroeconomic announcements, and corporate restructuring (CR) news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. Three types of macro announcements occurring at 8.30AM (i.e. Employees on Nonfarm Payroll, Core CPI and Producer Price Index) are obtained from the Haver database. The "*Before*" sample consists of the two days before news events. The "*After*" sample consists of the day of the news event, and the following day. The control sample ("*No-News*") constitutes the first 15 minutes of no-news days, obtained after excluding days with news and days with high returns. Days with news are the two days before and after earnings, macro or CR news. High return days are the 30% of days with the highest value of ACLCL, which is the absolute value of excess returns from the previous day's closing price to the current day's closing price. Excess returns are computed relative to the S&P 500 returns for the NYSE stocks and the Wilshire 5000 returns for the Nasdaq stocks. ** (*) indicate significance, at the 1% (5%) level or less, of the difference in means or medians between the test sample and the control sample. The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002.

	NYSE stocks						Nasdaq stocks					
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	No-news		Before		After		No-news		Before		After	
Before and After Earnings Reports												
N	5,558		445		435		5,954		449		451	
HILO	0.51	0.39	0.55	0.37	0.71**	0.51**	0.79	0.65	0.82	0.70	1.15**	0.92**
PEBAS	0.20	0.10	0.21	0.11	0.24	0.13**	0.10	0.08	0.11	0.08	0.11	0.09*
NTR	18	11	17	10	24**	12	130	49	134	51	249**	93**
AIMB	37	30	35	30	32**	23**	33	25	34	26	28**	21**
Before and After 8:30AM Macroeconomic Announcements												
N	5,558		2,749		2,884		5,954		2,875		2,999	
HILO	0.51	0.39	0.53	0.41	0.54*	0.41**	0.79	0.65	0.83**	0.69**	0.85**	0.70**
PEBAS	0.20	0.10	0.20	0.11**	0.20	0.11**	0.10	0.08	0.10	0.08	0.11*	0.08
NTR	18	11	18	10	19	11	130	49	137	54	142**	54*
AIMB	37	30	38	33	37	30	33	25	32	25	32	25
Before and After CR News												
N	5,558		152		187		5,954		114		116	
HILO	0.51	0.39	0.54	0.42	0.55	0.43	0.79	0.65	0.79	0.63	0.84	0.66
PEBAS	0.20	0.10	0.19	0.12**	0.17	0.13**	0.10	0.08	0.08**	0.06**	0.08**	0.06**
NTR	18	11	12**	10*	15*	11*	130	49	182**	80**	175**	133**
AIMB	37	30	38	33	37	29	33	25	27*	23	29	20

Table III: Correlation of Buyer and Seller-Initiated Trades Around News Events

The table reports the mean and median of the correlation between *ZBUY* and *ZSELL*, where:

$$ZBUY = \frac{BUY - Mean(BUY)}{SD(BUY)} \quad (1)$$

$$ZSELL = \frac{SELL - Mean(SELL)}{SD(SELL)} \quad (2)$$

The variable *BUY* (*SELL*) is the number of buyer-initiated (seller-initiated) trades in 5-minute time intervals, "Mean" is the sample mean of *BUY* or *SELL* and SD is the sample standard deviation of *BUY* or *SELL*. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The mean and median correlation is shown in Panel A for the first 15 minutes of days before and after news events: earnings reports, macroeconomic announcements, or corporate restructuring (CR) news. The "*No-news*" sample (i.e. the first 15 minutes of no-news days) is obtained after excluding days with news and days with high returns. Days with news are the two days before and after earnings, macro or CR news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. Three types of macro announcements occurring at 8.30AM (i.e. Employees on Nonfarm Payroll, Core CPI and Producer Price Index) are obtained from the Haver database. High return days are the 30% of days with the highest value of ACLCL, which is the absolute value of excess returns from the previous day's closing price to the current day's closing price. Excess returns are computed relative to the S&P 500 returns for the NYSE stocks and the Wilshire 5000 returns for the Nasdaq stocks.

The "*Before*" sample consists of the two days before news events. The "*After*" sample consists of the day of the news event, and the following day. The *dispersion* of analysts' forecasts is the SD of forecasts divided by the absolute mean (for earnings) or median (for macro announcements) forecast; the upper 50 percentile of dispersions are defined as *large dispersions*; the remaining forecasts are *small dispersions*. For earnings and macro news in the "*Before*" sample, we show results separately for large (LA) and small (SM) forecast dispersions. The *earnings surprise* is defined as the actual EPS minus the median earnings forecast, divided by the SD of surprises for the stock. The *announcement surprise* for an announcement type is the difference between the first reported value and the median macro forecast, divided by the SD of surprises for that type. *Large surprises* are those in the upper 50 percentile of the surprise distribution; the remaining surprises are *small surprises*. For earnings and macro news in the "*After*" sample, we show results separately for LA and SM surprises, and for LA and SM pre-news dispersions.

** (*) indicates that the mean and median correlations are significantly different at the 1% (5%) level or less for the before or after samples versus the no-news sample; or for the SM versus LA dispersions or surprises. The median correlations are compared using the Wilcoxon test. The mean correlations are compared using Fisher's z transformation.

In Panel B, we show the *exact p*-values $p+$ and $p-$ for the Kolmogorov-Smirnov one-sided test statistics $D+$ and $D-$, respectively. A low value for $p+$ ($p-$) implies that the correlation distribution in the before or after sample lies significantly below (above) the distribution in the no-news sample, indicating greater one-sidedness (two-sidedness) of the before or after sample. When comparing LA versus SM dispersions or surprises, a low value for $p+$ ($p-$) implies that the correlation distribution in the SM sample lies significantly below (above) the distribution in the LA sample. The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002.

Table III: Correlation of Buyer and Seller-Initiated Trades Around News Events

	NYSE stocks						Nasdaq stocks					
	Earnings		Macro		CR		Earnings		Macro		CR	
Panel A: Mean and Median Correlation												
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
No-news	0.34	0.36	0.34	0.36	0.34	0.36	0.48	0.49	0.48	0.49	0.48	0.49
Before	0.24*	0.27	0.33	0.32	0.36	0.39	0.31**	0.32*	0.47	0.50	0.32*	0.39
Before, LA dispersion	0.37	0.47	0.35	0.40	---	---	0.38	0.35	0.49	0.58	---	---
Before, SM dispersion	0.07**	0.15*	0.29	0.29	---	---	0.25	0.26	0.38**	0.35*	---	---
After	0.45*	0.51**	0.34	0.33	0.53**	0.65	0.58**	0.62**	0.47	0.53	0.41	0.55
After, LA surprise	0.46	0.60	0.37	0.36	---	---	0.68	0.81	0.47	0.51	---	---
After, SM surprise	0.42	0.51	0.31	0.32	---	---	0.51**	0.64	0.41*	0.43	---	---
After, LA pre-news dispersion	0.52	0.58	0.36	0.35	---	---	0.70	0.78	0.41	0.41	---	---
After, SM pre-news dispersion	0.43	0.56	0.32	0.28	---	---	0.50**	0.59*	0.47	0.46	---	---
Panel B: *P*-Values for Kolmogorov-Smirnov Tests of Differences in Correlation Distribution												
	p+	*p-*	*p+*	*p-*	*p+*	*p-*	*p+*	*p-*	*p+*	*p-*	*p+*	*p-*
Before vs. No-News	0.05	0.21	0.54	0.69	0.62	0.62	0.03	0.80	0.43	0.68	0.25	0.70
Before, SM vs. LA dispersion	0.02	0.92	0.14	0.90	---	---	0.05	0.66	0.02	0.91	---	---
After vs. No-News	0.42	0.00	0.68	0.68	0.89	0.04	0.67	0.01	0.55	0.55	0.46	0.45
After, SM vs. LA surprise	0.13	0.44	0.09	0.91	---	---	0.17	0.97	0.30	0.91	---	---
After, SM vs. LA pre-news dispersion	0.39	0.56	0.14	0.80	---	---	0.04	0.96	0.68	0.20	---	---

Table IV: Sorting Stocks Based on Sidedness: Liquidity, Volatility and Trading

The table shows the difference in the means and medians of volatility, liquidity, number of trades and the order imbalance for less and more two-sided stocks. The sample is 41NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002. The trading day is divided into intervals of 5-minute duration. Statistics are shown for the first 15 minutes of days before and after news events: earnings reports (Panel A), macroeconomic announcements (Panel B), or corporate restructuring (CR) news (Panel C). The control group is "*No-news*" (i.e. the 15 minutes of no-news days). No-news days are obtained after excluding days with news and days with high returns. Days with news are the two days before and after earnings, macro or CR news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. Three types of macro announcements occurring at 8.30AM (i.e. Employees on Nonfarm Payroll, Core CPI and Producer Price Index) are obtained from the Haver database. High return days are the 30% of days with the highest value of ACLCL, which is the absolute value of excess returns from yesterday's closing price to today's closing price. Excess returns are computed relative to the S&P 500 returns for the NYSE stocks and the Wilshire 5000 returns for the Nasdaq stocks.

The "*Before*" sample consists of the two days before news events. The "*After*" sample consists of the day of the news event, and the following day. The *dispersion* of analysts' forecasts is the standard deviation (SD) of forecasts divided by the absolute mean (for earnings) or median (for macro announcements) forecast; the upper 50 percentile of dispersions are defined as *large dispersions*; the remaining forecasts are *small dispersions*. For the "*Before*" sample, we show the difference in means and medians between earnings and macro forecasts with small and large dispersions (*Bef: SM-LA dis*). The *earnings surprise* is defined as the actual EPS minus the median earnings forecast, divided by the SD of surprises for the stock. The *announcement surprise* for an announcement type is the difference between the first reported value and the median macro forecast, divided by the SD of surprises for that type. *Large surprises* are those in the upper 50 percentile of the surprise distribution; the remaining are *small surprises*. For earnings and macro news in the "*After*" sample, we show the difference in means and medians between with small and large surprises (*Aft: SM-LA sur*), and between small and large pre-news dispersions (*Aft: SM-LA dis*). A positive number for a statistic indicates a higher value for small compared to large dispersions or surprises.

To determine sidedness, we estimate the correlation between *ZBUY* and *ZSELL*, where *ZBUY*= [*BUY-Mean(BUY)*]/*SD(BUY)* and *ZSELL*= [*SELL-Mean(SELL)*]/*SD(SELL)*. *BUY* (*SELL*) is the number of buyer-initiated (seller-initiated) trades in 5-minute time intervals, determined using the Lee-Ready (1991) algorithm. "Mean" and SD are the sample mean and standard deviation, respectively, of *BUY* or *SELL*. *Less (more) 2-sided* stocks are those with correlation less than (greater than or equal to) the median correlation for all stocks in the control sample. "*L-M*" indicates the difference in the means and medians of the various statistics for less 2-sided and more 2-sided stocks. A positive number for a statistic indicates a higher value for less two-sided stocks. ** (*) indicate significance, at the 1% (5%) level or less, of the difference in means or medians between intervals with less two-sided trading and intervals with more two-sided trading, or between large and small dispersions or surprises.

The variable *DIFN* is the difference in the number of 5-minute intervals between less and more two-sided stocks, or between small and large dispersions or surprises, as a percent of the total number of 5-minute intervals. *HILO* is ratio of the highest to the lowest price in an interval, minus 1. For an interval, *NTR* is total number of trades. The absolute order imbalance, *AIMB*, is the absolute value of (*BUY-SELL*)/*NTR*. The average proportional effective bid-ask half-spread in an interval, *PEBAS*, is defined as *Q**(*P- M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point. All estimates except *NTR* and *CORR* are multiplied by 100.

Table IV: Sorting Stocks Based on Sidedness: Liquidity, Volatility and Trading

Panel A: Before and after earnings reports

	NYSE stocks						Nasdaq stocks					
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	No-news: L-M		Before: L-M		Bef: SM-LA dis		No-news: L-M		Before: L-M		Bef: SM-LA dis	
DIFN	---		11%		2%		---		36%		-2%	
HILO	0.05**	0.01	-0.27*	-0.06*	-0.44**	-0.21**	-0.39**	-0.34**	-0.15*	-0.19**	-0.27**	-0.26**
PEBAS	0.00	0.04**	0.08	0.01	0.02	-0.06	0.01**	0.00**	0.03**	0.01*	0.01	0.01
NTR	-6**	-5**	-3*	-5	-4*	-6*	-162**	-112**	-183**	-160**	-168**	-129**
AIMB	6**	8**	15**	18**	8**	8*	15**	13**	15**	16**	6*	8*
	After: L-M		Aft: SM-LA sur		Aft: SM-LA dis		After: L-M		Aft: SM-LA sur		Aft: SM-LA dis	
DIFN	-33%		-2%		-1%		-52%		-1%		-1%	
HILO	0.01	-0.08	-0.04	-0.02	-0.27**	-0.17**	-0.40**	-0.35**	-0.03	-0.05	-0.23**	-0.33**
PEBAS	-0.06	0.01	-0.07	0.02	0.03	-0.05**	0.02**	0.02**	0.03**	0.02**	0.00	-0.01
NTR	5	-6	-6	-4	-7*	-9**	-252**	-115**	-164**	-79**	-254**	-154**
AIMB	10**	15**	2	2	6*	3	13**	14**	7**	7**	6**	6*

Panel B: Before and after 8:30AM macro announcements

	NYSE stocks						Nasdaq stocks					
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	No-news: L-M		Before: L-M		Bef: SM-LA dis		No-news: L-M		Before: L-M		Bef: SM-LA dis	
DIFN	---		13%		-8%		---		-4%		-8%	
HILO	0.05**	0.01	-0.18**	-0.13**	0.04	0.01	-0.39**	-0.34**	-0.33**	-0.34**	0.06**	0.07**
PEBAS	0.00	0.04**	0.02	0.02**	0.00	0.00	0.01**	0.00**	0.02**	0.01**	0.00	0.00
NTR	-6**	-5**	-7**	-7**	1	0	-162**	-112**	-182**	-136**	5	2
AIMB	6**	8**	10**	8**	0	0	15**	13**	15**	14**	-1	0
	After: L-M		Aft: SM-LA sur		Aft: SM-LA dis		After: L-M		Aft: SM-LA sur		Aft: SM-LA dis	
DIFN	17%		-4%		5%		-8%		-4%		4%	
HILO	-0.07**	-0.06**	0.03	0.03	0.03	0.01	-0.27**	-0.28**	0.03	0.07**	0.04	0.04
PEBAS	0.05**	0.01**	-0.01	0.01**	0.02	0.00	0.03**	0.01**	0.00	0.00	-0.01	0.00
NTR	0	-5**	0	0	1	0	-168**	-108**	3	3	18*	5
AIMB	7**	8**	0	3	2	1	14**	13**	-1	0	-1	-2

Panel C: Before and after CR news

	NYSE stocks						Nasdaq stocks					
	No-news: L-M		Before: L-M		After: L-M		No-news: L-M		Before: L-M		After: L-M	
DIFN	---		51%		-81%		---		5%		-40%	
HILO	0.05**	0.01	0.08	-0.01	-0.33**	-0.25**	-0.39**	-0.34**	-0.22*	-0.18*	-0.48**	-0.31**
PEBAS	0.00	0.04**	-0.05	0.00	-0.06	-0.04*	0.01**	0.00**	0.03**	0.05**	0.01	0.01
NTR	-6**	-5**	-3	-2	-12**	-8**	-162**	-112**	-170**	-162**	-170**	-183**
AIMB	6**	8**	5	8	13	21	15**	13**	15**	15**	14**	16*

Table V: Autocorrelation Statistics for Sidedness, the Bid-Ask Spread, Volatility, and the Number of Trades

The table shows the autocorrelation at lag 1 for sidedness, volatility, liquidity, and the number of trades. To determine sidedness, we estimate the correlation *CORR* between *ZBUY* and *ZSELL*, where *ZBUY*= [*BUY-Mean(BUY)*]/*SD(BUY)* and *ZSELL*= [*SELL-Mean(SELL)*]/*SD(SELL)*. *BUY* (*SELL*) is the number of buyer-initiated (seller-initiated) trades in 5-minute time intervals, "Mean" and SD are the sample mean and standard deviation, respectively, of *BUY* or *SELL*. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. Volatility is measured by *HILO*, the ratio of the highest to the lowest price in an interval minus 1. *NTR* is total number of trades. *PEBAS* is the average proportional effective bid-ask half-spread in an interval, defined as *Q**(*P*- *M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point.

Statistics are shown for the first 15 minutes of days before and after news events (i.e. earnings reports, macroeconomic announcements, or CR news). CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. Three types of macro announcements occurring at 8.30AM (i.e. Employees on Nonfarm Payroll, Core CPI and Producer Price Index) are obtained from the Haver database. The "*Before*" sample consists of the two days before an earnings or macro report or CR news. The "*After*" sample consists of the day of the earnings or macro report or CR news, and the following day.

The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002. ** (*) indicate, at the 1% (5%) level or less, whether the coefficient estimates are significantly different from zero.

	HILO		*PEBAS*		*CORR*		*NTR*	
	Est	*t*-stat	Est	*t*-stat	Est	*t*-stat	Est	*t*-stat
No-news days, All stocks								
Autocorrelation	0.43**	53.19	0.35**	43.06	0.54**	66.32	0.82**	100.4
Before CR news, All stocks								
Autocorrelation	0.17**	3.11	0.18**	3.24	-0.22**	-4.03	0.78**	14.43
Before earnings and macro news, NYSE stocks								
Autocorrelation	0.15**	9.82	0.27**	17.37	0.27**	17.08	0.72**	45.65
Before earnings and macro news, Nasdaq stocks								
Autocorrelation	0.60**	39.60	0.35**	23.06	0.39**	26.18	0.84**	55.77
After CR news, all stocks								
Autocorrelation	0.24**	4.74	0.39**	7.71	-0.16**	-3.16	0.76**	14.96
After earnings and macro news, NYSE stocks								
Autocorrelation	0.36**	23.33	0.37**	23.98	0.15**	9.62	0.73**	47.23
After earnings and macro news, Nasdaq stocks								
Autocorrelation	0.62**	41.78	0.37**	25.05	0.40**	27.31	0.84**	56.74

Table VI: Simultaneous Equation Results: Sidedness, the Bid-Ask Spread, Volatility, and the Number of Trades

The table shows results from a simultaneous equation system involving sidedness, volatility, liquidity, and the number of trades. To determine sidedness, we estimate the correlation *CORR* between *ZBUY* and *ZSELL*, where *ZBUY*= [*BUY-Mean(BUY)*]/*SD(BUY)* and *ZSELL*= [*SELL-Mean(SELL)*]/*SD(SELL)*. *BUY* (*SELL*) is the number of buyer-initiated (seller-initiated) trades in 5-minute time intervals, "Mean" and SD are the sample mean and standard deviation, respectively, of *BUY* or *SELL*. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. Volatility is measured by *HILO*, the ratio of the highest to the lowest price in an interval minus 1. *NTR* is total number of trades. *PEBAS* is the average proportional effective bid-ask half-spread in an interval, defined as *Q**(*P*- *M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point.

Statistics are shown for the first 15 minutes of days before (Panel A) and after (Panel B) news events (i.e. earnings reports, macroeconomic announcements, or CR news). CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. Three types of macro announcements occurring at 8.30AM (i.e. Employees on Nonfarm Payroll, Core CPI and Producer Price Index) are obtained from the Haver database. The "*Before*" sample consists of the two days before an earnings or macro report or CR news. The "*After*" sample consists of the day of the earnings or macro report or CR news, and the following day. The *dispersion* of analyst forecasts is the SD of forecasts divided by the absolute mean (for earnings) or median (for macro announcements) forecast. The *earnings surprise* is defined as the actual EPS minus the median earnings forecast, divided by the SD of surprises for the stock. The *announcement surprise* for an announcement type is the difference between the first reported value and the median macro forecast, divided by the SD of surprises for that type.

The estimation method used is the Two Stage Least Squares (2SLS). In the first stage, the endogenous variables *EV*={*CORR*, *HILO*, *NTR*, *PEBAS*} are regressed on instrumental variables *IV*, which are the first lags of *EV*. For earnings and macro news, we also include in *IV* the dummy variable *DIS*/*SUR*. For earnings and macro news, *DIS*/*SUR* is 1 for the upper 50 percentile of the distribution of *DISPERSION* (*SURPRISE*) in the "*Before*" ("*After*") sample, and is 0 otherwise. Let the fitted values of *EV* from the first stage regression be *E(CORR)*, *E(HILO)*, *E(NTR)*, and *E(PEBAS)*. Let *L1X* denote the first lag of variable *X*. The second stage regressions for interval *i*, stock *j* and day *t* are:

$$CORR_{ijt} = a_0 L1CORR_{ijt} + a_1 E(PEBAS)_{ijt} + a_2 E(HILO)_{ijt} + a_3 E(NTR)_{ijt} + e1_{ijt} \quad (1)$$
$$PEBAS_{ijt} = b_0 L1PEBAS_{ijt} + b_1 E(CORR)_{ijt} + b_2 E(HILO)_{ijt} + b_3 E(NTR)_{ijt} + e2_{ijt} \quad (2)$$
$$HILO_{ijt} = c_0 L1HILO_{ijt} + c_1 E(CORR)_{ijt} + c_2 E(PEBAS)_{ijt} + c_3 E(NTR)_{ijt} + e3_{ijt} \quad (3)$$
$$NTR_{ijt} = d_0 L1NTR_{ijt} + d_1 E(CORR)_{ijt} + d_2 E(PEBAS)_{ijt} + d_3 E(HILO)_{ijt} + e4_{ijt} \quad (4)$$

e1 to *e4* are the error terms. For earnings and macro news, we also include *DIS*/*SUR* as a pre-determined variable in (1)-(4). *HILO* is multiplied by 100 and *NTR* is divided by 1000 to make the estimates easier to read. The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002. ** (*) indicate, at the 1% (5%) level or less, whether the coefficient estimates are significantly different from zero.

Table VI, Panel A: Before News Events
First Stage Regression Results from 2SLS estimation

Instrumental Variable	*HILO* Est	*HILO* *t*-stat	*PEBAS* Est	*PEBAS* *t*-stat	*CORR* Est	*CORR* *t*-stat	*NTR* Est	*NTR* *t*-stat
No-news days, all stocks								
L1CORR	0.18**	7.61	-0.03*	-2.02	0.67**	58.48	0.04**	13.61
Adj R^2, N	0.25	7,238	0.32	7,238	0.43	7,238	0.80	7,238
Before CR news, all stocks								
L1CORR	0.38**	3.48	0.01	0.17	-0.47**	-2.69	0.02	0.80
Adj R^2, N	0.21	168	0.11	168	0.05	168	0.74	168
Before earnings and macro news, NYSE stocks								
L1CORR	0.09**	3.61	-0.02	-0.69	0.16**	7.09	0.01**	7.34
Adj R^2, N	0.15	1,866	0.06	1,866	0.06	1,866	0.63	1,866
Before earnings and macro news, Nasdaq stocks								
L1CORR	0.16**	6.04	-0.01	-1.79	0.30**	14.69	0.02**	4.86
Adj R^2, N	0.27	2,140	0.47	2,140	0.23	2,140	0.81	2,140

Second Stage Regression Results from 2SLS estimation

	No-news days		Before CR news		Before earnings and macro news			
Explanatory	All stocks		All stocks		NYSE stocks		Nasdaq stocks	
Variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
Dependent variable: *CORR*								
Intercept	-0.02**	-2.96	0.14	0.60	-0.03	-0.95	0.14**	5.41
L1CORR	0.64**	50.92	-0.54*	-2.37	0.13**	5.51	0.25**	10.77
E(PEBAS)	-0.13**	-7.81	-0.82	-0.39	-0.09	-0.87	-1.20**	-5.44
E(NTR)	0.16**	5.61	0.90	1.08	2.90**	3.22	0.27**	3.31
DISPERSION	---	---	---	---	0.06**	2.97	0.10**	6.21
E(HILO)	0.13**	9.52	0.16	0.37	0.11	1.52	0.23**	5.18
Adj R^2, N	0.42	7,238	0.05	168	0.07	1,866	0.23	2,140
Dependent variable: *PEBAS*								
Intercept	0.06**	8.31	0.08**	3.04	0.10**	3.08	0.03**	7.37
L1PEBAS	0.36**	54.91	0.14**	2.80	0.27**	8.62	0.50**	26.06
E(CORR)	-0.04	-1.83	0.02	0.31	-0.12	-0.64	-0.03**	-2.68
E(NTR)	-0.08*	-2.44	-0.26*	-2.13	-1.93	-1.85	-0.05**	-4.51
DISPERSION	---	---	---	---	0.01	0.46	0.00	1.65
E(HILO)	0.02	1.33	0.05	0.89	0.13	1.65	0.03**	4.85
Adj R^2, N	0.33	7,238	0.12	168	0.07	1,866	0.48	2,140
Dependent variable: *HILO*								
Intercept	0.25**	21.83	0.27	1.12	0.22**	6.57	0.14**	3.46
L1HILO	0.25**	36.78	0.17**	2.65	0.17**	9.48	0.26**	13.74
E(CORR)	0.23**	6.58	-0.77*	-2.10	0.51*	2.46	0.53**	5.47
E(PEBAS)	0.16**	4.95	0.44	0.23	0.47**	4.14	1.26**	4.31
E(NTR)	0.53**	9.78	1.38*	2.18	4.14**	3.39	0.43**	4.27
DISPERSION	---	---	---	---	-0.04	-1.44	-0.09**	-3.77
Adj R^2, N	0.26	7,238	0.09	168	0.14	1,866	0.26	2,140
Dependent variable: *NTR*								
Intercept	0.01**	5.85	0.05	1.53	0.01**	6.11	0.03**	4.21
L1NTR	0.65**	110.34	0.68**	7.04	0.67**	21.30	0.70**	48.61
E(CORR)	0.07**	12.81	-0.04	-0.68	0.03**	4.52	0.09**	4.15
E(PEBAS)	0.00	0.01	-0.26	-0.98	-0.00	-0.21	-0.08	-1.19
DISPERSION	---	---	---	---	-0.00	-1.41	-0.01*	-2.12
E(HILO)	-0.03**	-7.81	-0.01	-0.11	-0.00	-1.07	-0.05**	-3.41
Adj R^2, N	0.77	7,238	0.67	168	0.44	1,866	0.74	2,140

Table VI, Panel B: After News Events
First Stage Regression Results from 2SLS estimation

Instrumental Variable	*HILO* Est	*HILO* *t*-stat	*PEBAS* Est	*PEBAS* *t*-stat	*CORR* Est	*CORR* *t*-stat	*NTR* Est	*NTR* *t*-stat
No-news days, all stocks								
L1CORR	0.18**	7.61	-0.03*	-2.02	0.67**	58.48	0.04**	13.61
Adj R^2, N	0.25	7,238	0.32	7,238	0.43	7,238	0.80	7,238
After CR news, all stocks								
L1CORR	-0.45**	-5.07	-0.02	-1.04	-0.29**	-2.77	0.01	0.83
Adj R^2, N	0.32	187	0.18	187	0.08	187	0.82	187
After earnings and macro news, NYSE stocks								
L1CORR	0.07**	2.73	-0.00	-0.04	0.11**	5.34	0.00**	3.44
Adj R^2 N	0.23	1,930	0.11	1,930	0.03	1,930	0.64	1,930
After earnings and macro news, Nasdaq stocks								
L1CORR	0.09**	3.23	-0.01**	-4.22	0.30**	14.70	0.01*	2.16
Adj R^2, N	0.27	2,254	0.49	2,254	0.21	2,254	0.84	2,254

Second Stage Regression Results from 2SLS estimation

	No-news days		After CR news		After earnings and macro news			
Explanatory	All stocks		All stocks		NYSE stocks		Nasdaq stocks	
Variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
Dependent variable: *CORR*								
Intercept	-0.02**	-2.96	-0.02	-0.09	0.04	1.30	0.10**	3.95
L1CORR	0.64**	50.92	-0.14	-1.05	0.11**	5.04	0.26**	11.58
E(PEBAS)	-0.13**	-7.81	3.74	1.68	0.19	1.90	-1.16**	-5.66
E(NTR)	0.16**	5.61	0.54	0.61	0.77	1.09	0.17*	2.46
SURPRISE	---	---	---	---	0.07**	3.87	0.10**	5.96
E(HILO)	0.13**	9.52	0.20	0.91	0.02	0.39	0.26**	5.89
Adj R^2, N	0.42	7,238	0.08	187	0.03	1,930	0.20	2,254
Dependent variable: *PEBAS*								
Intercept	0.06**	8.31	0.08**	3.18	0.08**	3.52	0.03**	6.44
L1PEBAS	0.36**	54.91	0.13*	2.29	0.21**	12.66	0.56**	25.88
E(CORR)	-0.04	-1.83	-0.00	-0.02	-0.06	-0.36	-0.05**	-4.28
E(NTR)	-0.08*	-2.44	-0.22*	-2.36	-2.13**	-4.34	-0.02	-1.75
SURPRISE	---	---	---	---	0.02	0.86	0.01*	2.39
E(HILO)	0.02	1.33	0.03	0.56	0.17**	4.01	0.03**	3.64
Adj R^2, N	0.33	7,238	0.21	187	0.12	1,930	0.48	2,254
Dependent variable: *HILO*								
Intercept	0.25**	21.83	0.18	0.42	0.23**	7.12	0.22**	5.98
L1HILO	0.25**	36.78	0.23	1.40	0.27**	14.20	0.25**	14.64
E(CORR)	0.23**	6.58	1.85*	2.04	0.48*	2.10	0.33**	3.59
E(PEBAS)	0.16**	4.95	-5.25	-0.96	0.22	1.92	1.40**	5.74
E(NTR)	0.53**	9.78	-0.33	-0.22	4.84**	7.27	0.50**	6.59
SURPRISE	---	---	---	---	-0.07*	-2.35	-0.10**	-4.83
Adj R^2, N	0.26	7,238	0.07	187	0.22	1,930	0.29	2,254
Dependent variable: *NTR*								
Intercept	0.01**	5.85	0.05**	2.83	0.01**	5.76	0.05**	7.04
L1NTR	0.65**	110.34	0.59**	14.62	0.73**	32.60	0.68**	65.67
E(CORR)	0.07**	12.81	-0.02	-0.19	0.02**	2.77	0.03	1.43
E(PEBAS)	0.00	0.01	-0.20	-0.66	0.00	0.03	-0.21**	-3.80
SURPRISE	---	---	---	---	-0.00*	-2.18	-0.01	-1.27
E(HILO)	-0.03**	-7.81	-0.00	-0.00	-0.00	-0.36	-0.01	-1.17
Adj R^2, N	0.77	7,238	0.81	187	0.56	1,930	0.83	2,254

Table VII: Results for the Opening Minutes of Days without News

The table reports results for the opening minutes of trading on *no-news* days and a control sample called "*Mid-day*" (i.e. the period from 12 PM to 3 PM of no-news days). No-news days are obtained after excluding days with news and days with high returns. Days with news are the two days before and after earnings, macro or corporate restructuring (CR) news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. The macro announcements are Employees on Nonfarm Payroll, Core CPI and Producer Price Index), all occurring at 8.30AM, and obtained from the Haver database. High return days are the 30% of days with the highest value of ACLCL, which is the absolute value of excess returns from the yesterday's closing price to today's closing price. Excess returns are computed relative to the S&P 500 returns for the NYSE stocks and the Wilshire 5000 returns for the Nasdaq stocks.

Panel A shows, for the opening 5 minutes, the means and medians of *HILO*, *NTR*, *AIMB* and *CORR*. *HILO* is the ratio of the highest to the lowest price in the interval, minus 1; *NTR* is the number of trades; *AIMB* is the absolute value of (*BUY-SELL*)/*NTR*, where *BUY* (*SELL*) is the number of buyer (seller) initiated trades; and *PEBAS* is the average proportional effective bid-ask half-spread in an interval, defined as *Q**(*P- M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point. *CORR* is the correlation between *ZBUY* and *ZSELL*, where *ZBUY*= [*BUY-Mean(BUY)*]/*SD(BUY)* and *ZSELL*= [*SELL-Mean(SELL)*]/*SD(SELL)*, where "Mean" and SD are the sample mean and standard deviation of *BUY* or *SELL*. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. Estimates for *HILO*, *PEBAS* and *AIMB* are multiplied by 100.

Panel B shows, for the opening 5 minutes, the difference in the means and medians of *HILO*, *PEBAS*, *NTR* and *AIMB* for less versus more two-sided stocks. *Less (more) 2-sided* stocks are those with correlation less than (greater than or equal to) the median correlation for all stocks in the control sample. "*L-M*" indicates the difference in the means and medians of the various statistics for less 2-sided and more 2-sided stocks. A positive number for a statistic indicates a higher value for less two-sided stocks. *DIFN* is the difference in the number of intervals between less and more two-sided stocks, as a percent of the total number of 5-minute intervals.

Panels C and D show results for the opening 15 minutes. Panel C reports the autocorrelation at lag 1 of *CORR*. In Panel D, we present results from estimating a simultaneous equation system using the Two Stage Least Squares (2SLS) method. In the first stage regression, the endogenous variables *EV*={*CORR*, *HILO*, *NTR*, *PEBAS*} are regressed on the first lags of *EV*, denoted by {*L1CORR*, *L1HILO*, *L1NTR*, *L1PEBAS*}. For the opening minutes, we divide the first 15 minutes of the day into three 5-minute intervals. For the "*Mid-day*" sample, we divide the 12PM to 3PM into hourly intervals. Let the fitted values of *EV* from the first-stage regressions be denoted by {*E(CORR)*, *E(HILO)*, *E(NTR)*, *E(PEBAS)*}. The second stage regressions for interval *i*, stock *j* and day *t* are:

$$CORR_{ijt} = a_0 L1CORR_{ijt} + a_1 E(PEBAS)_{ijt} + a_2 E(HILO)_{ijt} + a_3 E(NTR)_{ijt} + e1_{ijt} \quad (1)$$

$$PEBAS_{ijt} = b_0 L1PEBAS_{ijt} + b_1 E(CORR)_{ijt} + b_2 E(HILO)_{ijt} + b_3 E(NTR)_{ijt} + e2_{ijt} \quad (2)$$

$$HILO_{ijt} = c_0 L1HILO_{ijt} + c_1 E(CORR)_{ijt} + c_2 E(PEBAS)_{ijt} + c_3 E(NTR)_{ijt} + e3_{ijt} \quad (3)$$

$$NTR_{ijt} = d_0 L1NTR_{ijt} + d_1 E(CORR)_{ijt} + d_2 E(PEBAS)_{ijt} + d_3 E(HILO)_{ijt} + e4_{ijt} \quad (4)$$

e1 to *e4* are the error terms. *HILO* is multiplied by 100 and *NTR* is divided by 1000 to make the estimates easier to read. ** (*) indicates statistical significance at the 1% (5%) level or less. The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002.

Table VII: Results for the Opening Minutes of Days without News

Panel A: Descriptive Statistics

	NYSE stocks				Nasdaq stocks			
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	Mid-day		First 5 min		Mid-day		First 5 min	
N	49,265		1,239		51,762		1,437	
HILO	0.19	0.14	0.46**	0.30**	0.25	0.20	0.97**	0.82**
PEBAS	0.10	0.05	0.27**	0.13**	0.06	0.04	0.13**	0.10**
NTR	12	9	13*	5**	39	17	148**	53**
AIMB	44	33	41**	33**	45	38	31**	25**
CORR	0.15	0.13	0.33**	0.35**	0.30	0.26	0.41**	0.43**

Panel B: Sorting stocks by sidedness

	NYSE stocks				Nasdaq stocks			
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	Mid-day: L-M		First 5 min: L-M		Mid-day: L-M		First 5 min: L-M	
DIFN	---		-63%		---		-37%	
HILO	-0.01**	-0.03**	0.33**	0.33**	-0.06**	-0.09**	-0.27**	-0.24**
PEBAS	0.06**	0.01**	0.00	0.07	0.03**	0.01**	0.01	0.00
NTR	-5**	-4**	11**	8**	-33**	-24**	-126**	-53**
AIMB	9**	10**	2	1	16**	17**	13**	13

Panel C: Autocorrelation Statistics, Lag 1

	First 15 minutes				Mid-Day			
	NYSE stocks		Nasdaq stocks		NYSE stocks		Nasdaq stocks	
	Est	*t*-stat	Est	*t*-stat	Est	*t*-stat	Est	*t*-stat
CORR	0.15**	9.55	0.47**	30.93	0.64**	41.23	0.77**	50.95

Panel D: Second-stage regression results from 2SLS estimation

	First 15 minutes				Mid-Day			
	NYSE stocks		Nasdaq stocks		NYSE stocks		Nasdaq stocks	
Explanatory Variable	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Dependent variable: *CORR*								
L1CORR	0.13**	6.99	0.35**	20.59	0.63**	138.95	0.58**	97.28
E(PEBAS)	0.13**	4.31	-0.53**	-6.09	-0.07**	-16.00	-0.97**	-24.08
E(NTR)	1.97**	5.43	0.33**	9.54	2.35**	31.98	0.33**	10.99
E(HILO)	0.05	1.69	0.12**	6.86	0.02**	2.83	0.28**	16.94
Adj R^2, N	0.06	2,732	0.40	2,805	0.50	33,659	0.59	35,305
Dependent variable: *PEBAS*								
E(CORR)	0.34	1.55	-0.03*	-2.02	-0.04	-1.19	-0.05**	-18.92
Adj R^2, N	0.18	2,732	0.51	2,805	0.07	33,659	0.46	35,305
Dependent variable: *HILO*								
E(CORR)	0.42	1.65	0.70**	7.17	0.05**	2.93	0.31**	25.52
Adj R^2, N	0.16	2,732	0.31	2,805	0.11	33,659	0.24	35,305
Dependent variable: *NTR*								
E(CORR)	0.05**	5.52	0.15**	8.15	0.02**	20.63	0.15**	23.90
Adj R^2, N	0.49	2,732	0.77	2,805	0.44	33,659	0.31	35,305

Table VIII: Results for the Closing Minutes of Days without News

The table reports results for the closing minutes of trading on *no-news* days and a control sample called "*Mid-day*" (i.e. the period from 12 PM to 3 PM of no-news days). No-news days are obtained after excluding days with news and days with high returns. Days with news are the two days before and after earnings, macro or corporate restructuring (CR) news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. The macro announcements are Employees on Nonfarm Payroll, Core CPI and Producer Price Index), all occurring at 8.30AM, and obtained from the Haver database. High return days are the 30% of days with the highest value of ACLCL, which is the absolute value of excess returns from the yesterday's closing price to today's closing price. Excess returns are computed relative to the S&P 500 returns for the NYSE stocks and the Wilshire 5000 returns for the Nasdaq stocks.

Panel A shows, for the last 5 minutes, the means and medians of *HILO*, *NTR*, *AIMB* and *CORR*. We also show results for the last 5 minutes of no-news days when the bid-ask spread increases between 12 PM and 3PM ("*Last 5 min, inc spd*"). *HILO* is the ratio of the highest to the lowest price in the interval, minus 1; *NTR* is the number of trades; *AIMB* is the absolute value of (*BUY-SELL*)/*NTR*, where *BUY* (*SELL*) is the number of buyer (seller) initiated trades; and *PEBAS* is the average proportional effective bid-ask half-spread in an interval, defined as *Q**(*P- M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point. *CORR* is the correlation between *ZBUY* and *ZSELL*, where *ZBUY*= [*BUY-Mean(BUY)*]/*SD(BUY)* and *ZSELL*= [*SELL-Mean(SELL)*]/*SD(SELL)*, where "Mean" and SD are the sample mean and standard deviation of *BUY* or *SELL*. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. Estimates for *HILO*, *PEBAS* and *AIMB* are multiplied by 100.

Panel B shows, for the last 5 minutes, the difference in the means and medians of *HILO*, *PEBAS*, *NTR* and *AIMB* for less versus more two-sided stocks. *Less (more) 2-sided* stocks are those with correlation less than (greater than or equal to) the median correlation for all stocks in the control sample. "*L-M*" indicates the difference in the means and medians of the various statistics for less 2-sided and more 2-sided stocks. A positive number for a statistic indicates a higher value for less two-sided stocks. *DIFN* is the difference in the number of intervals between less and more two-sided stocks, as a percent of the total number of 5-minute intervals.

Panels C and D show results for the closing 15 minutes. Panel C reports the autocorrelation at lag 1 of *CORR*. In Panel D, we show, for the last 15 minutes, results from estimating a simultaneous equation system using the Two Stage Least Squares (2SLS) method. In the first stage regression, the endogenous variables *EV*={*CORR*, *HILO*, *NTR*, *PEBAS*} are regressed on the first lags of *EV*, denoted by {*L1CORR*, *L1HILO*, *L1NTR*, *L1PEBAS*}. For the closing minutes, we divide the last 15 minutes of the day into three 5-minute intervals. For the "*Mid-day*" sample, we divide the 12PM to 3PM into hourly intervals. Let the fitted values of *EV* from the first-stage regressions be denoted by *E(CORR)*, *E(HILO)*, *E(NTR)*, *E(PEBAS)*}. The second stage regressions for interval *i*, stock *j* and day *t* are:

$$CORR_{ijt} = a_0 L1CORR_{ijt} + a_1 E(PEBAS)_{ijt} + a_2 E(HILO)_{ijt} + a_3 E(NTR)_{ijt} + e1_{ijt} \quad (1)$$

$$PEBAS_{ijt} = b_0 L1PEBAS_{ijt} + b_1 E(CORR)_{ijt} + b_2 E(HILO)_{ijt} + b_3 E(NTR)_{ijt} + e2_{ijt} \quad (2)$$

$$HILO_{ijt} = c_0 L1HILO_{ijt} + c_1 E(CORR)_{ijt} + c_2 E(PEBAS)_{ijt} + c_3 E(NTR)_{ijt} + e3_{ijt} \quad (3)$$

$$NTR_{ijt} = d_0 L1NTR_{ijt} + d_1 E(CORR)_{ijt} + d_2 E(PEBAS)_{ijt} + d_3 E(HILO)_{ijt} + e4_{ijt} \quad (4)$$

e1 to *e4* are the error terms. *HILO* is multiplied by 100 and *NTR* is divided by 1000 to make the estimates easier to read. ** (*) indicates statistical significance at the 1% (5%) level or less. The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002.

Table VIII: Results for the Closing Minutes of Days without News

Panel A: Descriptive Statistics

	NYSE stocks						Nasdaq stocks					
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	Mid-day		Last 5 min		Last 5 min, inc spd		Mid-day		First 5 min		Last 5 min, inc spd	
N	49,265		1,367		266		51,762		1,445		282	
HILO	0.19	0.14	0.31**	0.23**	0.34**	0.25**	0.25	0.20	0.60**	0.52**	0.53**	0.46**
PEBAS	0.10	0.05	0.12	0.06**	0.16*	0.07**	0.06	0.04	0.08**	0.07**	0.09**	0.07**
NTR	12	9	26**	22**	25**	19**	39	17	135**	73**	76**	48**
AIMB	44	33	32**	27**	32**	27**	45	38	30**	25**	35**	28**
CORR	0.15	0.13	0.05**	0.04**	0.13*	0.16**	0.30	0.26	0.33**	0.33**	0.31	0.27**

Panel B: Sorting stocks by sidedness

	NYSE stocks						Nasdaq stocks					
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
	Mid-day: L-M		Last 5 min: L-M		Last 5 min, inc spd: L-M		Mid-day: L-M		Last 5 min: L-M		Last 5 min, inc spd: L-M	
DIFN	-1%		30%		-13%		-3%		-40%		-5%	
HILO	-0.01**	-0.03**	0.09**	0.07**	-0.01	0.03	-0.06**	-0.09**	-0.09**	-0.08**	-0.05	-0.09
PEBAS	0.06**	0.01**	0.05	0.01	0.08	-0.02	0.03**	0.01**	0.01	0.02**	0.02**	0.02**
NTR	-5**	-4**	0	6**	3	7**	-33**	-24**	-80**	-45**	-60**	-34**
AIMB	9**	10**	0	1	8*	11**	14**	15**	8**	8**	14**	10**

Panel C: Autocorrelation Statistics, Lag 1

	Last 15 minutes				Mid-Day			
	NYSE stocks		Nasdaq stocks		NYSE stocks		Nasdaq stocks	
	Est	*t*-stat	Est	*t*-stat	Est	*t*-stat	Est	*t*-stat
CORR	0.17	10.74	0.23	14.96	0.42	4.61	0.55	6.13

Panel D: Second-stage regression results from 2SLS estimation

	Last 15 minutes				Mid-Day			
	NYSE stocks		Nasdaq stocks		NYSE stocks		Nasdaq stocks	
Explanatory Variable	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics	Estimate	*t*-statistics
Dependent variable: *CORR*								
L1CORR	0.24**	12.28	0.12**	5.83	0.63**	138.95	0.58**	97.28
E(PEBAS)	0.01	0.31	-0.32*	-2.21	-0.07**	-16.00	-0.97**	-24.08
E(NTR)	-0.14	-0.47	0.29**	6.78	2.35**	31.98	0.33**	10.99
E(HILO)	-0.07*	-2.23	0.05	1.66	0.02**	2.83	0.28**	16.94
Adj R^2, N	0.07	2,728	0.08	2,873	0.50	33,659	0.59	35,305
Dependent variable: *PEBAS*								
E(CORR)	-0.12	-0.85	0.03	0.96	-0.04	-1.19	-0.05**	-18.92
Adj R^2, N	0.16	2,728	0.62	2,873	0.07	33,659	0.46	35,305
Dependent variable: *HILO*								
E(CORR)	-0.29**	-3.19	1.27**	4.35	0.05**	2.93	0.31**	25.52
Adj R^2, N	0.26	2,728	0.28	2,873	0.11	33,659	0.24	35,305
Dependent variable: *NTR*								
E(CORR)	-0.01*	-2.28	0.27**	3.98	0.02**	20.63	0.15**	23.90
Adj R^2, N	0.73	2,728	0.66	2,873	0.44	33,659	0.31	35,305

Table IX: Results for Volume-Based Measure of Sidedness

The table reports results using the absolute volume imbalance (*VIMB*) as a measure of sidedness. *VIMB* is equal to the absolute value of (*BVOL-SVOL*)/*TVOL*, where *BVOL* (*SVOL*) is the volume of buyer (seller) initiated trades and *TVOL=BVOL+SVOL*. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. Estimates for *HILO*, *PEBAS* and *AIMB* are multiplied by 100.

Panel A shows the mean and median of *VIMB* for the first and last 5-minutes of trading on days on *no-news* days and a control sample called "*Mid-day*" (i.e. the period from 12 PM to 3 PM of no-news days). No-news days are obtained after excluding days with news and days with high returns. Days with news are the two days before and after earnings, macro or corporate restructuring (CR) news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. Earnings report dates, actual and analysts' most recent forecasts of quarterly earnings per share (EPS) are taken from the I/B/E/S database. The macro announcements are Employees on Nonfarm Payroll, Core CPI and Producer Price Index), all occurring at 8.30AM, and obtained from the Haver database. High return days are the 30% of days with the highest value of ACLCL, which is the absolute value of excess returns from the yesterday's closing price to today's closing price. Excess returns are computed relative to the S&P 500 returns for the NYSE stocks and the Wilshire 5000 returns for the Nasdaq stocks. Panel B shows the mean and median of *VIMB* for the first 15 minutes of no-news days and days before and after news events: earnings reports, macro announcements and CR news.

The "*Before*" sample consists of the two days before news events. The "*After*" sample consists of the day of the news event, and the following day. The *dispersion* of analysts' forecasts is the SD of forecasts divided by the absolute mean (for earnings) or median (for macro announcements) forecast; the upper 50 percentile of dispersions are defined as *large dispersions*; the remaining forecasts are *small dispersions*. For earnings and macro news in the "*Before*" sample, we show results separately for large (LA) and small (SM) forecast dispersions. The *earnings surprise* is defined as the actual EPS minus the median earnings forecast, divided by the SD of surprises for the stock. The *announcement surprise* for an announcement type is the difference between the first reported value and the median macro forecast, divided by the SD of surprises for that type. *Large surprises* are those in the upper 50 percentile of the surprise distribution; the remaining surprises are *small surprises*. For earnings and macro news in the "*After*" sample, we show results separately for large (LA) and small (SM) surprises.

Panel C shows results from a simultaneous equation system involving *VIMB*, *HILO*, *PEBAS* and *NTR*. *HILO* is the ratio of the highest to the lowest price in an interval minus 1. *NTR* is the total number of trades. *PEBAS* is the average proportional effective bid-ask half-spread in an interval, defined as *Q**(*P*-*M*)/*M*, where *P* is the trade price, *Q* is +1 (-1) for a buyer (seller) initiated trade and *M* is the quote mid-point. The estimation method used is the Two Stage Least Squares (2SLS). In the first stage, the endogenous variables *EV*={*VIMB*, *HILO*, *NTR*, *PEBAS*} are regressed on instrumental variables *IV*, which are the first lags of *EV*. For earnings and macro news, we also include in *IV* the dummy variable *DIS*/*SUR*. For earnings and macro news, *DIS*/*SUR* is 1 for the upper 50 percentile of the distribution of *DISPERSION* (*SURPRISE*) in the "*Before*" ("*After*") sample, and is 0 otherwise. Let the fitted values of *EV* from the first stage regression be *E(VIMB)*, *E(HILO)*, *E(NTR)*, and *E(PEBAS)*. Let *L1X* denote the first lag of variable *X*. The second stage regressions for interval *i*, stock *j* and day *t* are:

$$VIMB_{ijt} = a_0 L1VIMB_{ijt} + a_1 E(PEBAS)_{ijt} + a_2 E(HILO)_{ijt} + a_3 E(NTR)_{ijt} + e1_{ijt} \quad (1)$$

$$PEBAS_{ijt} = b_0 L1PEBAS_{ijt} + b_1 E(VIMB)_{ijt} + b_2 E(HILO)_{ijt} + b_3 E(NTR)_{ijt} + e2_{ijt} \quad (2)$$

$$HILO_{ijt} = c_0 L1HILO_{ijt} + c_1 E(VIMB)_{ijt} + c_2 E(PEBAS)_{ijt} + c_3 E(NTR)_{ijt} + e3_{ijt} \quad (3)$$

$$NTR_{ijt} = d_0 L1NTR_{ijt} + d_1 E(VIMB)_{ijt} + d_2 E(PEBAS)_{ijt} + d_3 E(HILO)_{ijt} + e4_{ijt} \quad (4)$$

e1 to *e4* are the error terms. For earnings and macro news, we also include *DIS*/*SUR* as a pre-determined variable in (1)-(4). The sample is 41 NYSE stocks and a matched sample of 41 Nasdaq stocks during January 2, 2003 to May 31, 2003. The NYSE and Nasdaq stocks are matched according to their closing price and market value on December 31, 2002. ** (*) indicates statistical significance at the 1% (5%) level or less.

Table IX: Results for Volume-Based Measure of Sidedness

Panel A: Volume imbalance statistics, first and last 5 Minutes of no-news days

	NYSE stocks						Nasdaq stocks					
	Mid-Day		First 5 min		Last 5 min		Mid-Day		First 5 min		Last 5 min	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
VIMB	55	55	49**	45**	45**	42**	51	49	35**	28**	36**	31**

Panel B: Volume imbalance statistics, first 15 Minutes around news events

	NYSE stocks						Nasdaq stocks					
	Earnings		Macro		CR		Earnings		Macro		CR	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
No-news	48	43	48	43	48	43	37	30	37	30	37	30
Before	47	44**	50**	47**	52	50**	37	30	37	30	31*	26**
Before, LA dispersion	42	40	51	49	---	---	32	25	37	29	---	---
Before, SM dispersion	52**	50**	49	45	---	---	41**	36**	36	30	---	---
After	44*	41**	47	43	51	50**	32**	25**	37	29**	32*	25**
After, LA surprise	39	33	48	43	---	---	28	23	38	31	---	---
After, SM surprise	48**	46**	47	42	---	---	36**	28**	35**	28*	---	---

Panel C: Second-stage regression results from 2SLS estimation, Before and After News

	Before earnings and macro news				After earnings and macro news			
	NYSE stocks		Nasdaq stocks		NYSE stocks		Nasdaq stocks	
	Dependent variable: *VIMB*							
Explanatory variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
DISPERSION/ SURPRISE	-0.01	-0.56	0.00	0.20	-0.02	-1.87	-0.01	-0.79
Adj R^2, N	0.07	1,893	0.23	2,148	0.06	1,972	0.20	2,263

Figure 1: Correlation Distribution before Earnings Reports

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days before earnings reports, and separately for reports with small and large divergences of analyst opinions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

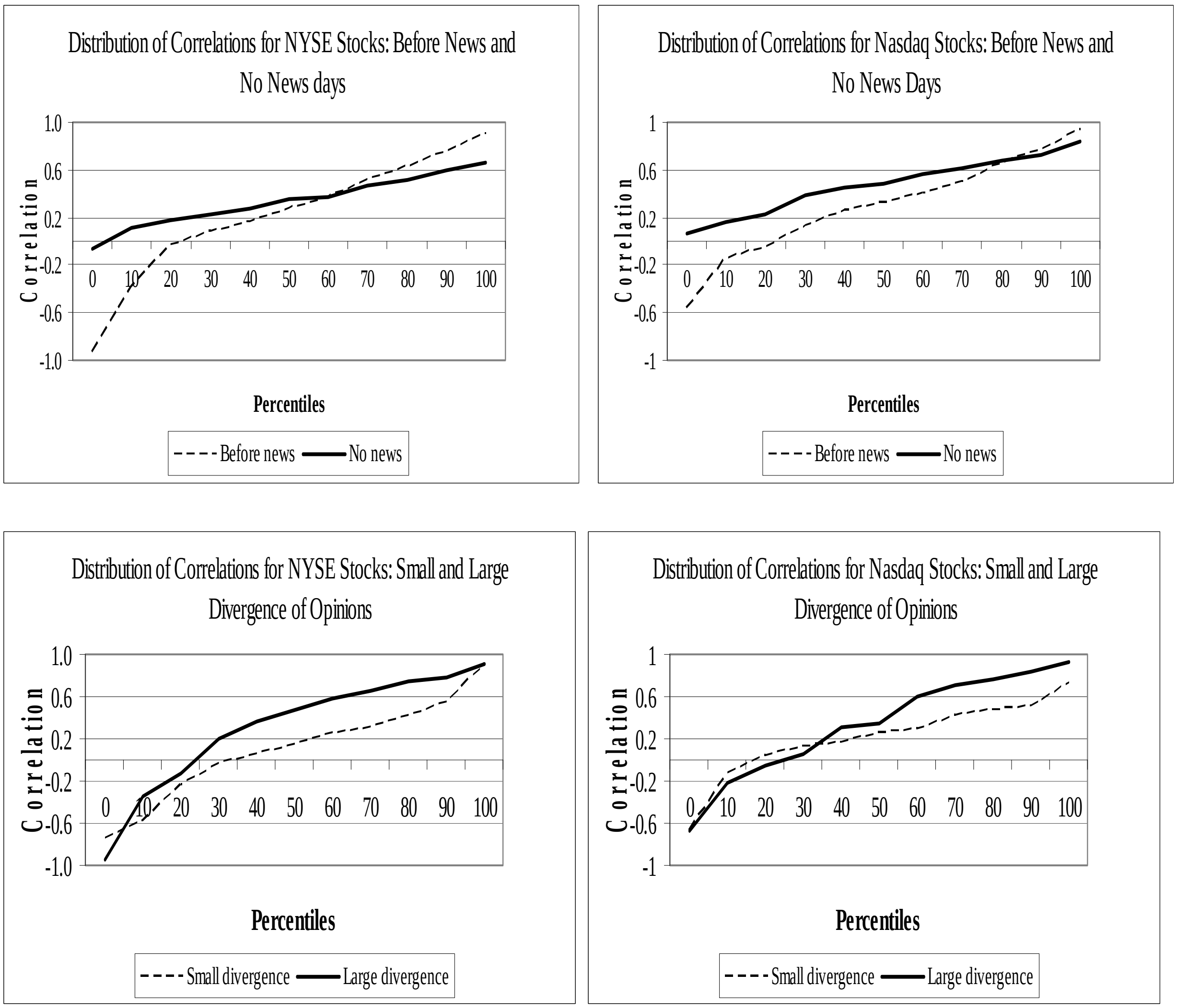

Figure 2: Correlation Distribution after Earnings Reports

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days after earnings reports. The figure also plots the correlation distribution for reports with small and large earnings news surprises, and for small and large pre-news analyst forecast dispersions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

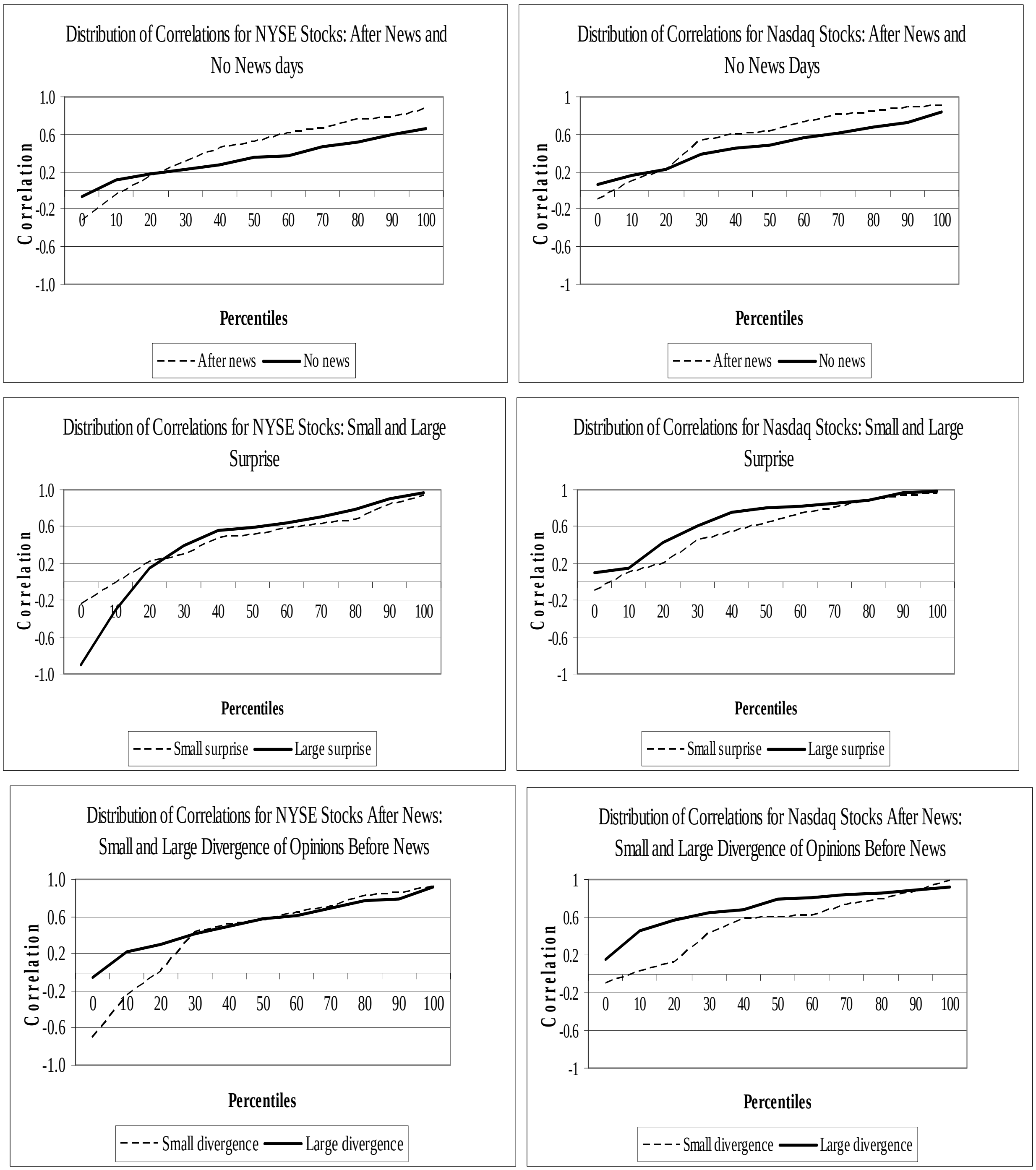

Figure 3: Correlation Distribution before Macroeconomic Announcements

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days before macro announcements, separately for reports with small and large divergences of analyst opinions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

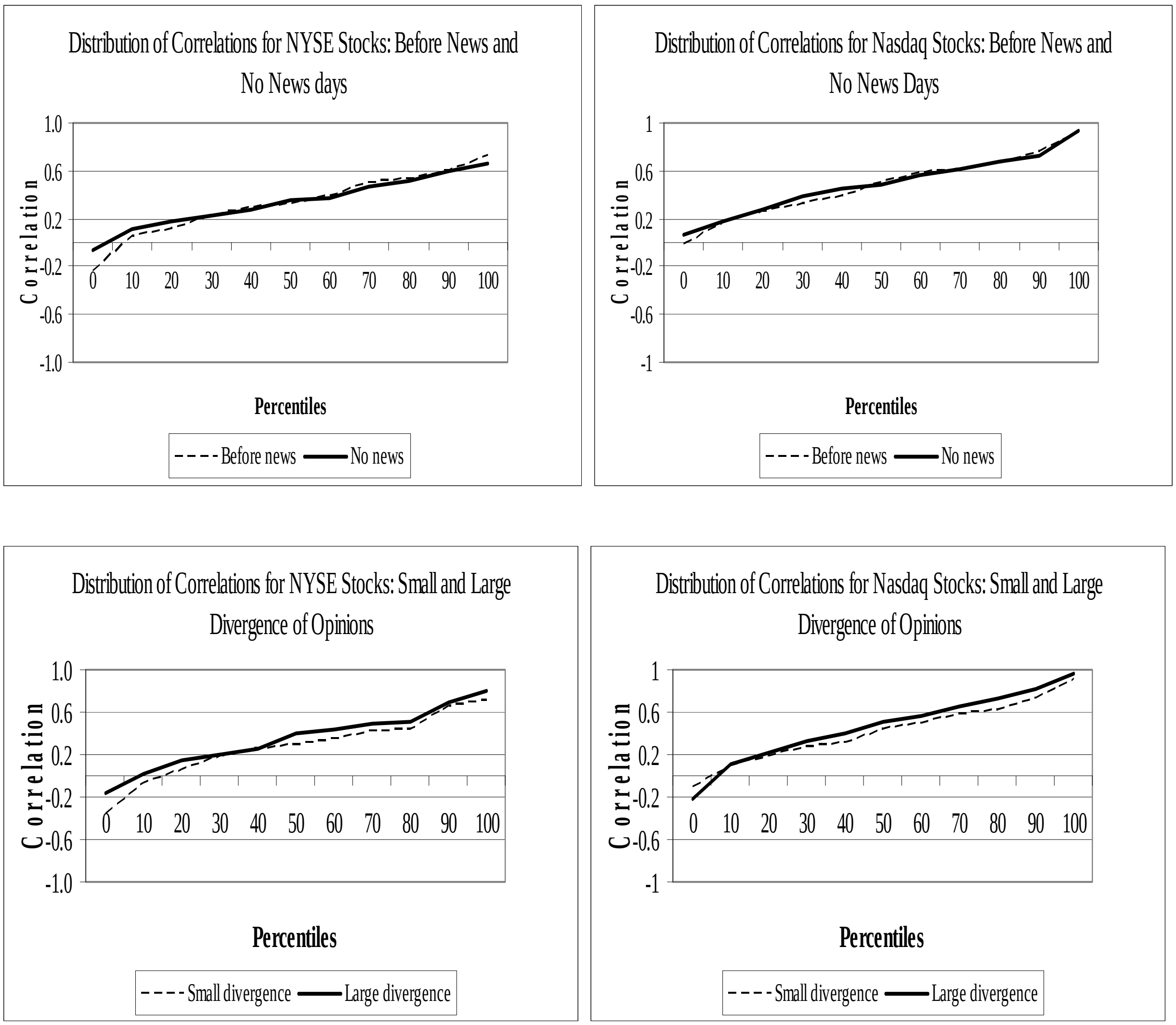

Figure 4: Correlation Distribution after Macroeconomic Announcements

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days after macroeconomic announcements. It also plots the correlation distribution for reports with small and large macro news surprises, and for small and large pre-news analyst forecast dispersions. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.

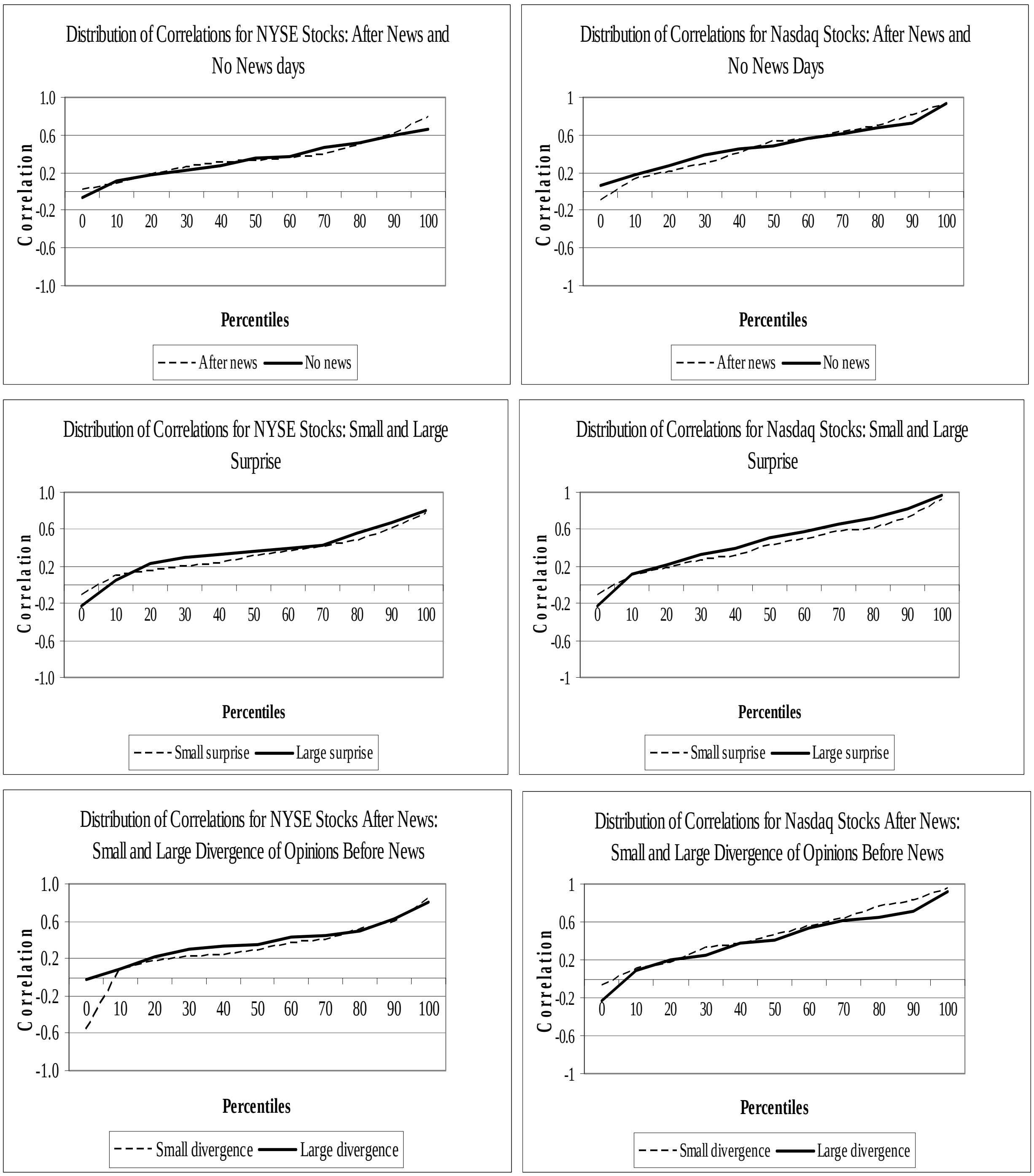

Figure 5: Correlation Distribution before and after CR News

The figure plots the distribution across stocks of the correlation between the numbers of buyer-initiated and low seller-initiated trades for the 2 days before and after corporate restructuring (CR) news. CR news days are identified by corporate news in major publications relating to mergers, share buybacks, divestitures, and joint ventures. The buyer- and seller-initiated trades are standardized by subtracting the sample mean and dividing by the sample standard deviation. Buyer and seller initiated trades are determined using the Lee-Ready (1991) algorithm. The sample is 41 NYSE stocks, and a matched sample of 41 Nasdaq stocks, during January 2, 2003 to May 31, 2003.