Does Public Financial News Resolve Asymmetric Information?

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Abstract

I test four predictions from a model in which a firm-specific news story releases previously privately held information, thereby expediting the market's absorption of a persistent liquidity shock. Using the entire Dow Jones archive to measure public news, I provide evidence consistent with these four predictions: 1) ten-day reversals of daily returns are 38% lower on news days; 2) ten-day volume-induced momentum in daily returns exists only on news days for many stocks; 3) the cross-sectional correlation between the absolute value of firms' abnormal returns and abnormal turnover is temporarily higher by 35% on news days; and 4) the price impact of order flow is temporarily lower by 4.5% on news days. Cross-sectional variation in the results suggests that news resolves more asymmetric information for small stocks and illiquid stocks.

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The goal of this paper is to assess how individual firms' information environments depend on the release of public financial news. Building on the insights from earlier market microstructure models, I propose and test a model in which the role of a public news story is to eliminate an information asymmetry between two groups of traders. Prior to the news, one investor group has superior information, but also incurs a liquidity shock. The news story informs the previously uninformed investor group, making them more willing to accommodate the liquidity shock. Even so, the uninformed investors do not fully accommodate the shock on the day of the news event.

This model has four empirical consequences for return predictability and trading activity. First, the return on the news day positively predicts returns after the news. The reason is that the gradual dissipation of the liquidity shock after the news leads to return momentum. Second, if news is an imperfect proxy for the release of information, the return on a high-volume news day positively predicts post-news returns. The reason is that trading volume is a complementary proxy for the resolution of asymmetric information and absorption of the liquidity shock. Third, the contemporaneous correlation between trading volume and the magnitude of price changes temporarily increases around news days. As news occurs, both volume and price changes are driven by the belief revisions of uninformed investors, who simultaneously learn that the stock's expected returns are higher and increase their stock holdings accordingly. Fourth, the price impact of informed trading temporarily decreases as news reduces information asymmetry. The theoretical model here is quite similar to the Kim and Verrecchia (1991), Wang (1994), Holden and Subrahmanyam (2002), and Llorente, Michaely, Saar, and Wang (2002) (hereafter LMSW) models, but differs in its explicit assumptions about the role and timing of a public news story.

This paper's central contribution is empirically testing the four predictions of this stylized model of news using data on stock returns and trading activity around public news releases. I measure public news using the entire Dow Jones (DJ) archive, which includes all DJ newswire and all Wall Street Journal (WSJ) stories about US firms with publicly traded stocks from 1979 to 2007. I compare stock returns and trading activity on news days and non-news days using daily cross-sectional regressions in the spirit of Fama and MacBeth (1973).

This analysis produces four main results: 1) ten-day reversals of daily returns are 38% lower on news days; 2) ten-day volume-induced momentum in daily returns exists only on news days for many stocks; 3) the cross-sectional correlation between the absolute value of firms' abnormal returns and abnormal turnover is temporarily higher by 35% on news days; and 4) the price impact of order flow is temporarily lower by 4.5% on news days. These findings suggest that public news is a proxy for information not yet fully incorporated in prices, but that some traders have already acted on this information, whereas other traders use news to learn about expected returns. To my knowledge, the second and third empirical findings are novel, whereas the first and fourth findings significantly extend previous results.

Although these four qualitative results are robust over time and across stocks with different characteristics, the magnitudes of the effects vary substantially. News is a better predictor of reduced return reversal in small firms, which suggests that each news story conveys more information for these firms. The link between news and reduced return reversal is also stronger for stories that consist of many newswire messages and earnings-related words, which are plausible proxies for the information content of news.

For small stocks and illiquid stocks, volume-induced return momentum occurs only on news days, whereas volume-induced reversal occurs on other days. This could indicate that public news resolves more asymmetric information in these firms. The correlation between absolute returns and volume declines by a larger amount following news stories that consist of many newswire messages and earnings-related words, and for small stocks and illiquid stocks. This suggests that the role of public information in resolving privately held differences in opinion is stronger for small stocks and illiquid stocks. Conversely, I find no clear evidence that news coincides with the arrival of liquidity shocks: for all firms and types of news, news does not predict increases in return reversals. One interpretation is that the release of news coincides with information more often than it coincides with liquidity shocks.

Several empirical design choices minimize the likelihood that the results are spurious. First, I focus on weekly time horizons for return reversals because the evidence in Jegadeesh (1990) and Lehmann (1990) shows that weekly return reversals dominate one-day autocorrelations. In these tests, I skip day one to avoid bid-ask bounce and other microstructure biases that affect return correlations in consecutive periods. Another benefit is that the return measurement period excludes the positive one-day autocorrelation that Sias and Starks (1997) link to institutional ownership. It is possible that institutional order splitting across days causes two-day price pressure that reverses at longer horizons. Indeed, recent evidence in Kaniel, Saar, and Titman (2007) and Barber, Odean, and Zhu (2009) demonstrates that price pressure from trading clienteles develops and subsides over multi-week horizons. Accordingly, I explicitly analyze whether institutional ownership affects the results.

Second, I present the four main results for firms in the top and bottom size and liquidity quintiles separately based on the LMSW (2002) findings that these stocks' information environments differ. Although the effects are often stronger for small and illiquid stocks, all four results hold in both groups. This demonstrates that the results are statistically robust and economically important. At the same time, the consistently stronger findings for small stocks and illiquid stocks hint at a role for information asymmetry.

Third, I use daily cross-sectional regressions—in the spirit of Fama and MacBeth (1973)—to control for a wide range of influences on firms' stock returns. For example, controlling for the well-known "high volume premium" of Gervais, Kaniel, and Mingelgrin (2001) is necessary to isolate the impact of volume-induced return momentum and public news releases, both of which are correlated with trading volume. The regressions also control for size, book-to-market, momentum, and volatility. I present these regressions separately for firms that differ according to alternative measures of the information environment such as analyst coverage and PIN—the probability of informed trading defined in Easley, Kiefer, O'Hara, and Paperman (1996)—to ensure that news is distinct from other proxies for information asymmetry.

This paper contributes to three literatures. One is the volume-induced return reversal literature, which includes a complex set of results. Whereas Conrad, Hameed, and Niden (1994) show that return reversals for relatively small Nasdaq stocks decrease with trading volume, Cooper (1999) shows that return reversals for large NYSE stocks increase with trading volume. Avramov, Chordia, and Goyal (2006) find that volume-induced return reversal increases with stock illiquidity. I confirm that large stocks and liquid stocks exhibit volume-induced momentum, whereas small stocks and illiquid stocks exhibit unconditional volume-induced reversals. I find, however, that small stocks and illiquid stocks actually exhibit volume-induced return momentum on public news days, just as large stocks and liquid stocks do on all days.

The findings here complement the volume-induced reversal findings in LMSW (2002). Whereas LMSW (2002) do not directly measure firms' information environments, I analyze the impact of public news releases on volume-induced and unconditional return reversals. I also investigate how the correlation between absolute returns and volume changes and how price impact changes around public news events. The upshot is that I provide new evidence on how investors obtain information that is relevant for firm valuation, and which public signals resolve information asymmetries across investors.

This paper also contributes to a growing literature on the impact of public news releases, which includes Stickel and Verrecchia (1994), Pritamani and Singal (2001), Chan (2003), Chae (2005), Vega (2006), Chava and Tookes (2007), Gutierrez and Kelley (2008), and Tetlock, Saar-Tsechansky, and Macskassy (2008). Of these papers, Chan (2003) and Gutierrez and Kelley (2008) are most closely related to this study. The first result in this paper extends the monthly and weekly findings in Chan (2003) and Gutierrez and Kelley (2008) to daily return reversals around public news. This is not trivial because the correlations between daily returns on news days and weekly and monthly returns surrounding public news are only 0.560 and 0.299, respectively. Interestingly, these correlations are 0.618 and 0.350 on news days with positive abnormal turnover, but just 0.321 and 0.120 on other news days. Neither Chan (2003) nor Gutierrez and Kelley (2008) explores this link between trading activity and returns on news days. By contrast, I analyze whether news predicts changes in volume-induced return momentum, the correlation between absolute returns and volume, and price impact.

This study differs from Stickel and Verrecchia (1994), Pritamani and Singal (2001), Vega (2006), Tetlock et al. (2008), and Tetlock (2009) because it compares high-frequency return reversals on news and non-news days. All of these earlier studies analyze reversals and momentum solely on news days, and the first three look at only earnings news.[1] This study's

[1] Stickel and Verrecchia (1994) show that post-earnings announcement drift (PEAD) increases with announcement-day trading volume. Vega (2006) shows that PEAD is higher for firms with low measures of PIN, differences of opinion on public news days, and low media coverage. Tetlock et al. (2008) shows that the words in public news

evidence on return predictability complements the evidence in Chae (2005) and Chava and Tookes (2007), which both mainly analyze trading volume around news events. This study differs from Tetlock et al. (2008) and Tetlock (2009) in its comparison of news and non-news events and its use of news data on the entire cross-section of publicly traded firms.

A third somewhat related literature examines intra-day responses to public information—e.g., Lee, Mucklow, and Ready (1993), Fleming and Remolona (1999), Green (2004), and Pasquariello and Vega (2007). The empirical focus of this paper on daily expected returns, correlations between returns and volume, and price impacts differs from the microstructure emphasis on intra-day spreads and depths. A key reason is that, although the news events in this sample have precise time stamps, these time stamps often do not correspond to the intra-day timing of the release of the underlying information event. Thus, I focus on daily market reactions to news because news usually occurs on the same day as the information event. A benefit of testing the daily expected return predictions of microstructure theory is that these predictions receive much less attention in the recent empirical literature on public information events.

Although this paper adopts an identification strategy based on rational market microstructure models, one could frame many of the empirical results as tests of behavioral asset pricing theories. The two classes of models are not mutually exclusive because specific behavioral biases could motivate the "liquidity" trading in microstructure models. For example, one could relate the results here on return reversals, volume-induced momentum, and the correlation between absolute returns and volume to predictions in the Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), or Hong and Stein (1999) over-

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releases predict firms' future cash flows and their stock returns, albeit briefly. Tetlock (2009) finds that news-day return reversal is higher when prior news, high return volatility, or high liquidity precedes the news day.

and underreaction models. For the most part, I do not emphasize this interpretation because the rational paradigm does a reasonable job of explaining the data.

I now provide a brief overview of the paper. In Section I, I introduce a simple model of how news resolves information asymmetries that makes four empirical predictions. In Section II, I describe the key empirical measures, and present several summary statistics. In Section III, I use regressions to assess the extent of return reversal and volume-induced reversal on news days and non-news days. I present the correlations between absolute returns and volume and the price impact results in Section IV. I provide a concluding discussion of the results in Section V.

I. A Stylized Model in Which Public News Resolves Information Asymmetry

The model here inherits its key economic features from Wang (1994) and LMSW (2002), but makes additional assumptions about the role and timing of public news stories. The model features three periods, two groups of investors, and one firm. One investor group (i) has a temporary informational advantage, but also incurs a privately observed liquidity (i.e., endowment) shock. The other investor group (u) is relatively uninformed, but is also completely rational. Each group is comprised of many investors who behave competitively as price takers. Both the informed and uninformed investor groups have CARA utility functions defined over consumption in period 3, after the liquidating dividend occurs. Their wealth levels do not affect the asset market equilibrium because of the CARA assumption. In each period, both investors choose how much to invest in the risky asset and a riskless asset. For simplicity, the safe asset pays a zero rate of return and there is no time discounting. The risky asset supply is normalized to one unit; and both investors' CARA risk aversion parameters are equal to one.

The informed investors (i) receive a signal in period 1 (s_1) about the firm's liquidating dividend ($d_3 = s_1 + e_3$) that occurs in time 3. The signal is normally distributed according to $s_1 \sim N(0, V_s)$ and the random component of the dividend is independently normally distributed according to $e_3 \sim N(d, V_e)$. The uninformed investors (u) observe the signal (s_1) when it is released publicly in a news announcement at time 2. In period 1, the informed investors incur a persistent liquidity shock to their endowments of stock holdings equal to n_1 per investor, which is normally distributed according to $n_1 \sim N(0, V_n)$. Although the uninformed investors do not observe this liquidity shock, they make rational inferences about its value based on the observed market price in period 1 (p_1) and the initially private signal (s_1) that becomes public in period 2. One interpretation of the model is that the uninformed investors are risk-averse market makers, who act competitively and rationally. A benefit of this interpretation is that one would expect the market makers to trade passively, allowing empirical researchers to use aggressive (i.e., signed) order flow as a proxy for the demand shocks from informed traders.

I compute the model's equilibrium using standard backward induction techniques. Denote investors' demand functions in each period by x_{it} and x_{ut}. From the CARA assumption, informed demand per investor, excluding the liquidity shock, is:

$$x_{it} = \frac{E_{it}(d_3) - p_t}{Var_{it}(d_3)}$$

where the it subscripts denote investor group i's conditional expectations and variances based on information available at time t. Demand for each investor in the uninformed group is:

$$x_{ut} = \frac{E_{ut}(d_3) - p_t}{Var_{ut}(d_3)}$$

To obtain the aggregate demands for the two groups, one multiplies the individual investor demands by the total sizes of each investor group, which are m for the informed group and $(1-m)$ for the uninformed group.

Demands in the second period, after s_1 is public, are particularly easy to compute:

$$x_{i2} = x_{u2} = \frac{d + s_1 - p_2}{V_e}$$

By setting demand equal to the unit supply, I obtain the equilibrium market price in period 2:

$$p_2 = d + s_1 - (1 - mn_1)V_e$$

The news release allows investors to perfectly infer the value of the private liquidity shock (n_1), making it effectively publicly observable. As in the Campbell, Grossman, and Wang (1993) model, a publicly observable liquidity shock temporarily depresses the market price.

I look for an equilibrium in the first period in which p_1 is linear in s_1 and n_1:

$$p_1 = d + a + b_s s_1 + b_n n_1$$

where I will determine the equilibrium values of the signal and liquidity shock coefficients (b_s and b_n) below. Anticipating the form of the pricing function, the uninformed investors use the observed price to learn about s_1 and n_1. Applying the market clearing condition in period 1, solving for the equilibrium price, and matching the three pricing coefficients on the constant, signal, and liquidity shock terms yields the solutions:

$$b_s = \left[1 - \frac{(1-m)V_e^2 V_n}{V_s + V_e^2 V_n + mV_e V_n} \right]$$

$$b_n = V_e\left[1 - \frac{(1-m)V_e^2 V_n}{V_s + V_e^2 V_n + mV_e V_n} \right]$$

$$a = -\frac{V_e(V_s + V_e^2 V_n + V_e V_n V_s)}{V_s + V_e^2 V_n + m V_e V_n V_s}$$

Applying the market clearing condition in period 0, when there is symmetric information and no liquidity shocks have occurred, the initial price is:

$$p_0 = d - (V_s + V_e)$$

One can use the pricing and demand equations above to determine returns and volume in periods 1 and 2. The relevant return is the difference in prices:

$$p_2 - p_1 = \frac{(1-m)V_e^3 V_n V_s}{V_s + V_e^2 V_n + m V_e V_n V_s} + \frac{(1-m)V_e^2 V_n}{V_s + V_e^2 V_n + m V_e V_n} s_1 - (1-m)V_e \frac{V_s + m V_e V_n}{V_s + V_e^2 V_n + m V_e V_n} n_1$$

The period 3 return is:

$$p_3 - p_2 = e - m n_1 V_e + V_e$$

The first important empirical prediction of the model is that the covariance between the (period 2) news announcement return and the (period 3) post-announcement return is positive:

$$Cov(p_3 - p_{2,} p_2 - p_1) = \frac{m(1-m)V_e^3 V_n^2}{V_s + V_e^2 V_n + m V_e V_n} > 0 \tag{1}$$

The reason is that news, by resolving information asymmetry in period 2, induces the uninformed investors to partially accommodate the (period 1) liquidity shock from informed investors. In period 3, the remainder of the liquidity shock dissipates. The gradual accommodation of the same (period 1) liquidity shock in periods 2 and 3 is what causes the positive covariance in returns in periods 2 and 3.

By contrast, the return in period 1 is:

$$p_1 - p_0 = -\frac{V_e(V_s + V_e^2 V_n + V_e V_n V_s)}{V_s + V_e^2 V_n + m V_e V_n V_s} + V_e + V_s + \left[\frac{V_s + m V_e^2 V_n + m V_e V_n}{V_s + V_e^2 V_n + m V_e V_n}\right] s_1 + \left[\frac{V_s + m V_e^2 V_n + m V_e V_n}{V_s + V_e^2 V_n + m V_e V_n}\right] V_e n_1$$

Based on the return equations above, the second empirical prediction of the model is that the covariance between (pre-news) returns in period 1 and period 2 is negative:

$$Cov(p_2 - p_{1,} p_1 - p_0) = -\frac{m(1-m)V_e^3 V_n^2 \left(V_s + mV_e^2 V_n + mV_e V_n\right)}{(V_s + V_e^2 V_n + mV_e V_n)^2} < 0 \qquad (2)$$

Overall, there is return reversal of non-news day returns (e.g., period 1) and return momentum for news-day (e.g., period 2) returns. More generally, there is higher return momentum (or lower return reversal) for news-day returns, as compared to non-news-day returns.

Next, I compute the trading volume in periods 1 and 2 (T_1 and T_2). The absolute value of the change in the informed investor group's holdings between periods 1 and 2 is:

$$T_2 = \frac{|\, p_1 - p_2 \,|}{V_e}$$

News-day trading volume is proportional to the magnitude of the market reaction to the news, implying that high trading volume coincides with informative news. In an empirical setting, some news stories could be irrelevant, meaning that news is an imperfect proxy for information. If so, one could use the occurrence of high trading volume as a complementary proxy, identifying news days that are more likely to coincide with the resolution of asymmetric information and absorption of the liquidity shock. Consequently, the model's second prediction is that returns on news days with high volume positively forecast post-news returns.

An even more direct implication of the trading volume equation is that volume is perfectly correlated with the absolute value of returns in the news announcement period:

$$Corr(T_2, |\, p_2 - p_1 \,|) = Corr\left(\frac{|\, p_1 - p_2 \,|}{V_e}, |\, p_2 - p_1 \,|\right) = 1 \qquad (3)$$

However, in the pre-news period, trading volume is:

$$T_1 = \left| \frac{d}{V_e + V_s} + \frac{(1-m)V_e V_n V_s}{V_s + V_e^2 V_n + mV_e V_n V_s} + \left[\frac{(1-m)V_e V_n}{V_s + V_e^2 V_n + mV_e V_n} \right](s_1 + V_e n_1) \right|$$

This implies that the correlation between volume and absolute returns in the pre-news period is:

$$Corr(T_1, | p_1 - p_0 |) < 1 \text{ if and only if } -a + V_s + \frac{V_e d}{V_e + V_s} \neq a(1-b_s)/b_s \qquad (4)$$

which is equivalent to $a/b_s - V_s - \frac{V_e d}{V_e + V_s} \neq 0$. Assuming that $m < 1$ and all other parameters are positive, this statement is always true because the left-hand side is negative:

$$a/b_s - V_s - \frac{V_e d}{V_e + V_s}$$
$$= -\frac{(1-m)^2 V_e^4 V_n^2 V_s}{(V_s + mV_e^2 V_n + mV_e V_n)(V_s + V_e^2 V_n + mV_e V_n V_s)} - \frac{V_e d}{V_e + V_s} < 0$$

Thus, trading volume in the non-news period (i.e., period 1) is imperfectly correlated with the absolute value of returns. The third prediction of the model is that trading volume and absolute returns are less positively correlated in the pre-news period than in the news period.

Lastly, I examine the price impact of informed trading, which is defined as the regression coefficient of returns on informed order flows. In the news period, price impact is:

$$\frac{Cov(p_2 - p_1, x_{2i} - x_{1i})}{Var(x_{2i} - x_{1i})} = \frac{Cov(p_2 - p_1, \frac{p_1 - p_2}{V_e})}{Var(\frac{p_1 - p_2}{V_e})} = -1 \qquad (5)$$

However, in the pre-news period, the price impact of informed trading is:

$$\frac{Cov(p_1 - p_0, x_{1i} - x_{0i})}{Var(x_{1i} - x_{0i})} = \frac{b_s}{1-b_s} Var(s_1 + V_e n_1) > 0$$
$$\text{because } b_s = \frac{V_s + mV_e^2 V_n + mV_e V_n}{V_s + V_e^2 V_n + mV_e V_n} < 1 \text{ when } m < 1$$

Of course, the extreme prediction that price impact will be negative in the news period is unlikely to hold in a more general model with some background information asymmetry that is not resolved by news. Instead, the more robust fourth prediction of the model is that the price impact of informed trading decreases as the asymmetric information is resolved. Empirically, I use the Lee and Ready (1991) algorithm for signing order flow to identify informed trades. This identification approach is valid if the informed group trades more aggressively than the uninformed group, who effectively act as market makers in this model.

II. Data Description

The primary data source is the Dow Jones (DJ) news archive, which contains all DJ News Service and all Wall Street Journal (WSJ) stories from 1979 to 2007. For each news story in the archive, there are often multiple newswire messages corresponding to separate paragraphs that DJ releases individually. I use the DJ firm code identifier at the beginning of each newswire to assess whether a story mentions a publicly traded US firm. Unfortunately, my manual review of the news stories prior to November 1996 reveals that stories without any firm codes sometimes mention US firms—i.e., the DJ firm codes contain measurement error. More seriously, DJ may back-fill firm codes prior to November 1996 in a systematic fashion that introduces survivorship bias in the data. This survivorship bias does not seem to affect stories after November 1996. Between 95% and 99% of sample firms have news coverage in each year after 1996.

Subperiod analyses—most of which appear in the tables that follow—show that all the main results hold before and after 1996. Using other subperiod cutoffs does not affect these findings. In general, the results are either similar or somewhat stronger in the 1997 to 2007 period, which is not subject to survivorship bias. Because this paper focuses on high-frequency return, volume, volatility, and news measures, survivorship bias in news coverage does not seem to strengthen the results.

Although the measures emphasized here do not depend heavily on accurate estimates of stocks' long-run expected returns, I examine the relationship between stocks' long-run returns and media coverage to gauge the importance of the survivorship bias. I am able to replicate the key Fang and Peress (2009) finding that one-month expected returns are lower for stocks with some media coverage. If anything, this effect is slightly larger in the current data set, which suggests that survivorship bias does not materially affect expected returns. This fact also mitigates broader concerns about survivorship bias because one-month returns are more likely than daily or weekly returns to show evidence of survivorship bias.

The main regression tests use data on news, returns, volume, and firm characteristics. The measure of firm-specific news coverage is an indicator variable ($News_{it}$ = 0 or 1) that is equal to one if firm *i*'s DJ code appears in any stories in the archive between the close of trading day $t - 1$ and the close of trading day t. I match the DJ firm codes to US ticker symbols in CRSP by trading date. I match each firm's news and returns data to accounting (CompuStat), analyst forecast (IBES), institutional holdings (Thomson 13f), and stock transaction data (TAQ).

The analysis below focuses on economically important firms with reliably measured trading returns. The sample includes only stocks with positive trading volume on all days from $t - 60$ to $t - 1$, and stocks with prices that exceed \$5 on day $t - 1$. These requirements eliminate many small and illiquid firms, most of which have very few news stories anyway. The sample includes only US firms with common equity (share codes 10 or 11 in CRSP) listed on the NYSE, NASDAQ, or Amex exchange. After imposing these requirements, 13,842 unique firms appear at some point in the 29-year sample. Of these firms, 9,452 have news stories on at least one trading day. This 68% coverage percentage is considerably higher than coverage in Fang and Peress (2009), but somewhat lower than coverage in Chan (2003). The missing firm codes in the pre-1997 DJ archive appear to account for the discrepancy with Chan (2003).

[Insert Figure 1 here.]

Figure 1 depicts the monthly average of the daily percentage of eligible firms covered in the DJ archive. Between two and five percent of firms appear in the archive on most days in the 1980s, whereas 20% to 35% of firms are mentioned on most days in the post-2000 period. I also compute three long-horizon coverage measures for trading days that meet the sample inclusion criteria: the percentage of firms with at least one news story in the current month; the percentage with news in the most recent 12 months; and the percentage of trading days in the most recent 12 months that a firm appears in the news for the firm at the 90th percentile. This last measure shows how news coverage evolves for the most widely followed firms. All four coverage measures increase over time, and the yearly coverage measure jumps to over 95% shortly after November of 1996. In 1980, news stories occur on 10% of trading days for the firm in the 90th percentile of coverage, but they occur on 60% of trading days in 2007.

III. The Impact of News on Return Reversals

A. Regression Estimates

In the model in Section I and in several related models, liquidity shocks predict larger return reversals and the release of information predicts smaller return reversals. To evaluate whether public news coincides with liquidity or informational shocks, I examine whether news on day *t* predicts a larger or smaller reversal of firm *i*'s day-*t* excess stock return (Ret_{it}). For simplicity, I define Ret_{it} as the firm's raw day-t return minus the value-weighted market return. The dependent variable is the firm's ten-day raw return from trading day t+2 through day t+10 ($Ret_{i,t+2,t+10}$), where I omit day t+1 to mitigate bid-ask bounce. The ten-day horizon matches earlier papers, such as Tetlock et al. (2008), that explore return momentum around news. The results are very similar with a five-day horizon. I define $Ret_{i,t+2,t+10}$ using raw returns for ease of interpretation. The results below are not sensitive to the specific risk benchmarks chosen partly because the regressions include controls for several firm characteristics and because short-horizon return predictability is often robust to benchmark selection (Fama (1998)).

The controls for firm characteristics that predict expected returns include monthly measures of firm size ($Size_{it}$), book-to-market (BM_{it}) ratio, yearly return momentum excluding the most recent calendar month (Mom_{it}), and average daily return volatility during the previous calendar month ($TVol_{it}$) using standard techniques. I define the size and book-to-market variables as in Fama and French (1992), the momentum variable as in Jegadeesh and Titman (1993), and the total volatility variable as in Ang, Hodrick, Xing, and Zhang (2006).[2] Most regression specifications include abnormal turnover ($Turn_{it}$) to control for the high volume return premium of Gervais, Kaniel, and Mingelgrin (2001). For consistency, I use the same turnover variable in the interaction terms below that measure volume-induced reversal. Thus, I use the abnormal turnover definition from Campbell, Grossman, and Wang (1993): the log of daily turnover (share volume over shares outstanding), detrended using a rolling 60-day average of log turnover.

In all regressions, the set of independent variables includes the news indicator ($News_{it}$) and an interaction between news and day-t excess returns ($news_{it}*Ret_{it}$). Because news coverage is strongly related to firm size (e.g., Chan (2003), Vega (2006), Engelberg (2008), and Fang and

[2] To reduce positive skewness, I compute the logarithms of the size, book-to-market, momentum, and volatility variables. I add constants (k) before computing the log of each variable (x) so that the slope of $\ln(k+x)$ is equal to one when x is evaluated at the variable's unconditional sample mean. This does not affect the results.

Peress (2009)), I include an additional variable ($size_{it}*Ret_{it}$) to control for possible interactions between size and reversals. To reduce multicollinearity with the size interaction ($Size_{it}*Ret_{it}$), I demean $News_{it}$ by size quintile on each day t before computing the news interaction term ($news_{it}*Ret_{it}$). I also demean $Size_{it}$ by the mean size for all firms in the sample on each day t before computing the size interaction term ($size_{it}*Ret_{it}$). Lowercase letters denote the demeaned news and size variables. Throughout this paper, I demean all independent variables before computing interaction terms. The only exceptions are abnormal turnover and excess returns, which both already have means approximately equal to zero by construction.

The regression includes an interaction term to control for volume-induced momentum ($Turn_{it}*Ret_{it}$) because news and volume are correlated. It also includes an interaction term between news and turnover ($news_{it}*Turn_{it}$) as a control, in case the high volume return premium depends on the occurrence of news. I also include a triple interaction term ($news_{it}*Turn_{it}*Ret_{it}$) to assess whether volume-induced return reversal depends on news. This coefficient estimate is the basis for testing two auxiliary predictions of the theory that news resolves asymmetric information: first, volume-induced return reversals (momentum) will be lower (higher) on days with news; and second, the impact of news on volume-induced return reversals will be larger for stocks with higher information asymmetry. The complete regression specification is:

$$Ret_{i,t+2,t+10} = a + b_1 * Ret_{it} + b_2 * news_{it}*Ret_{it} + b_3 * Turn_{it}*Ret_{it} + b_4 * news_{it}*Turn_{it}*Ret_{it} + c * Controls_{it} + e_{it} \text{ for all } i \text{ on each day } t \quad (6)$$

where $Controls_{it} = [News_{it}\ size_{it}*Ret_{it}\ news_{it}*Turn_{it}\ Turn_{it}\ Size_{it}\ BM_{it}\ Mom_{it}\ TVol_{it}]^T$ is an 8 by 1 column vector and c is a 1 by 8 row vector of coefficients. The news-related reversal and news-related volume-induced reversal coefficients (b_2 and b_4) are the focus of this section.

In the spirit of the Fama and MacBeth (1973) method for estimating expected returns, I estimate equation (6) daily using the cross-section of all firms on each day. Using data from all days increases the efficiency of the regression estimates relative to throwing away data (e.g., Hansen and Hodrick (1980)), which would be necessary if I used weekly or biweekly regressions. I compute the full sample coefficient estimate as the time series average of the daily cross-sectional regression coefficients.[3] Using an unweighted average disregards the standard error of each daily coefficient estimate, which is generally inefficient. Instead, I weight each daily coefficient estimate using the inverse of the variance of the daily coefficient as suggested in Ferson and Harvey (1999).[4] Because consecutive daily estimates are based on return observations with overlapping nine-day time horizons, the daily estimates of the cross-sectional regression coefficients are positively autocorrelated. Thus, I compute Newey-West (1987) standard errors that are robust to autocorrelation up to 10 daily lags and heteroskedasticity in the daily coefficient estimates. Using additional lags has no material impact on the inferences.

[Insert Table 1 here.]

Table 1 reports coefficient estimates for all variables in equation (6). The first key result is that the coefficient on the news interaction term ($news_{it}*Ret_{it}$) is positive, statistically significant, and economically significant. Reversals on days [2,10] of returns on day 0 are 4.2% lower when news occurs on day 0. By contrast, the size of the average reversal—represented by the coefficient on Ret_{it}—is 9.8% of the day 0 return. Using the coefficients on Ret_{it}, $news_{it}*Ret_{it}$, $news_{it}*Turn_{it}*Ret_{it}$, and $Turn_{it}*Ret_{it}$, along with the average values of $news_{it}$, $news_{it}*Turn_{it}$, and $Turn_{it}$ on news days and non-news days, the reversal on news and non-news days are equal to -6.4% and -10.2% of the daily return, respectively. This implies that the reversal of day 0 returns is 38% lower if news occurs on day 0. One can also compare the reversal sizes in basis points

[3] I ignore monthly estimates from months with fewer than 100 firm-days with news stories. This criterion binds only when I divide the sample by firm size, liquidity, analyst coverage, and other characteristics.
[4] Even though the standard error of each daily coefficient is biased downward, using the standard errors as weights does not induce a bias in the weighted average if the downward bias is proportional. The reason is that the average weighting cancels in the numerator and denominator of the weighted average.

rather than percentages of daily returns. The standard deviation of returns on news days is 3.85%, whereas the standard deviation on non-news days is 2.75%. Multiplying these standard deviations by the percentage reversals above, one sees that the news-day return reversal of 39 bps is over 31% lower than the non-news-day reversal of 56 bps. The observed difference of 17 bps in the news- and non-news return reversal understates the importance of public information arrival if the news indicator variable is a noisy proxy for public information. The results in subsequent tests that allow reversal to depend on public news characteristics support this view.

The second main result in Table 1 is that the regression coefficient on the $news_{it}*Turn_{it}*Ret_{it}$ variable is consistently positive, statistically significant, and economically significant. The fourth row in Table 1 shows five regression specifications that differ in whether they exclude earnings or non-earnings news and in which period they cover. The robustness in the $news_{it}*Turn_{it}*Ret_{it}$ coefficients indicates that neither earnings news nor survivorship bias drives the results. To gauge the economic impact of news on volume-induced momentum, consider an increase in turnover from the 10th to the 90th percentile of its distribution conditional on news. This increase in turnover leads to a 3.2% increase in momentum of daily returns on news days, but only a 0.5% increase in momentum of daily returns on non-news days. These percentages correspond to volume-induced momentum magnitudes of 19 bps and 3 bps over days [2,10] for news and non-news days, respectively. Together, the first and second key results imply that the average news story reduces return reversal, and that high-volume news stories reduce return reversal by an even larger amount.

[Insert Figure 2 here.]

To summarize these first two results, Figure 2 shows stylized calculations of the predicted percentage of a stock's daily return that is reversed in four situations: when news occurs ($news_{it}$ = 0.702) or does not occur ($news_{it}$ = -0.099), and when turnover conditional on news is high (90th percentile) or low (10th percentile). The four sets of bars in Figure 2 represent the predicted return reversal for all four combinations of news and non-news, and high and low turnover. The dark gray, light gray, and black bars show how these reversals change when the sample includes all news, excludes earnings news, and excludes non-earnings news.

Figure 2 provides a simple graphic interpretation of the first two empirical results. The fact that the first two sets of bars in Figure 2 are statistically and economically significantly lower than the second two sets of bars implies that news reduces return reversal on average. The second main result is that the difference between the third and fourth set of bars in Figure 2 is much larger than the difference between the first two sets of bars. This means that volume reduces return reversal, but only when it accompanies news. Equivalently, one could say that public news reduces return reversal by more when it accompanies high volume.

The numerous subsample results in Table 1 and Figure 2 demonstrate that the impacts of news on reversal and volume-induced momentum are both quite robust. For example, columns four and five in Table 1 show that the impact of news on reversals ($news_{it}*Ret_{it}$ coefficient) and volume-induced momentum ($news_{it}*Turn_{it}*Ret_{it}$ coefficient) remains similar regardless of the period. This is important because the amount of news changes dramatically from 1979 to 2007—see Figure 1—and because survivorship bias concerns do not apply to the 1997 to 2007 period.

Another possible concern is that the impact of news on reversal occurs only when news accompanies earnings announcements. If this were true, there is little incremental benefit to examining news stories beyond examining earnings news, which many other studies do already. To address this concern, the regression in column two excludes all the articles without earnings-related news, while the regression in column three excludes all the articles with earnings-related news. The definition of earnings-related news is the word-based measure in Tetlock et al. (2008): an indicator for stories that mention either "earnings" or any other word with the stem "earn." Using alternative definitions such as the DJ earnings subject code produces very similar results, but the DJ earnings subject codes do not exist prior to 1992.

The evidence in columns two and three suggests that earnings-related news has a greater impact on return reversal (8.4% of daily returns). Nevertheless, news that does not explicitly mention earnings has a large and statistically significant impact on reversal (2.9% of daily returns). Thus, non-earnings news is an important determinant of the information environment. The results on earnings-related news in Table 1 on Figure 2 are especially notable because several previous studies argue that earnings news is more informative than non-earnings news. For example, Tetlock et al. (2008) shows that earnings news elicits larger market reactions and is a better predictor of firms' cash flows. Comparing the coefficient on $news_{it}*Ret_{it}$ in rows two and three in Table 1, one sees that earnings-related news reduces return reversals by a larger amount than non-earnings news. However, a comparison of the two $news_{it}*Turn_{it}*Ret_{it}$ coefficients shows that earnings-related news does not reduce volume-induced return reversals by a larger amount than non-earnings news. One interpretation is that the average impact of news on reversal depends on the informativeness of the news, but the impact of high-volume news on reversal does not depend on news informativeness. This distinction will be important for understanding why the impact of news on volume-induced return momentum varies across firms.

The two other coefficients related to return reversals in Table 1 are the size and turnover interaction terms ($Turn_{it}*Ret_{it}$ and $size_{it}*Ret_{it}$). These coefficients show that reversals are significantly smaller for firms experiencing high abnormal turnover and for small firms. Controlling for the turnover interaction term reduces the magnitude of the news interaction term because turnover and news are positively correlated and both turnover and news reduce return reversals. Controlling for the size interaction term has the opposite impact on the news interaction term because size increases return reversals. The two main results above hold regardless of whether the regressions include these controls.

The coefficients on all five of the variables already known to predict expected returns have the expected signs in Table 1. The abnormal turnover ($Turn_{it}$) and return momentum (Mom_{it}) variables are the most quantitatively important of these five variables. The volatility effect is also a significant predictor of returns ($TVol_{it}$). However, the size and book-to-market ($Size_{it}$ and BM_{it}) effects are somewhat weaker, and only marginally significant. These findings are broadly consistent with other return predictability results for this sample period.

B. Using Firm and News Characteristics to Isolate the Impact of News

To assess how the impact of news on return reversal varies, I rerun the main regressions in equation (6) for subsamples sorted by firm size ($Size_{it}$) and four size-adjusted (*SA*) firm characteristics: stock illiquidity ($IlliquiditySA_{it}$), analyst coverage ($AnalystSA_{it}$), PIN ($PINSA_{it}$), and institutional ownership ($InstOwnSA_{it}$). I sort the sample on each trading day *t* into five quintiles using each of the variables above. Following Avramov, Chordia, and Goyal (2006), the illiquidity measure is the daily Amihud (2002) illiquidity measure averaged over trading day *t-4* through day *t*. The daily illiquidity measure is equal to $10^6 * |Ret_{it}| / (Volume_{it})$, where $Volume_{it}$ is the stock's dollar volume. The PIN measure is PIN for the most recent calendar year. These data come from Soeren Hvidkjaer's web site, which provides annual PIN measures for NYSE/Amex common stocks from 1983 to 2001 as described in Easley, Hvidkjaer, O'Hara (2005). Analyst coverage for each stock is the number of analysts with yearly earnings forecasts for that stock in the previous calendar month. A firm's institutional ownership is the sum of all institutional holdings divided by the firm's market capitalization at the end of each calendar quarter.

I also test whether the impact of news on reversal varies with the information content of news. I use the log of the number of distinct newswire messages (Msg_{it}) that occur for firm *i* on trading day *t* as an empirical proxy for information content. This variable is defined only on days in which a firm appears in the news. The idea behind Msg_{it} is that stories consisting of more newswire messages are more likely to be timely, important, and thorough.

Table 2 displays the monthly the cross-sectional correlations between daily media coverage, quarterly media coverage, size, illiquidity, analyst coverage, PIN, and institutional ownership, along with the newswire messages variable (Msg_{it}). The quarterly media coverage variable is the fraction of trading days in which a firm appears in the news during the three most recent calendar months. The correlations are based on the log transforms of the variables with highly positive skewness, which include quarterly media coverage, monthly analyst coverage variable, and weekly illiquidity.

[Insert Table 2 here.]

Nearly all of the pairwise correlations in Table 2 are highly statistically significant with the signs that one would expect. Specifically, media coverage is positively correlated with size, analyst coverage, and institutional ownership; and is negatively correlated with PIN and illiquidity. Firm size seems to be a mediating factor across all the pairwise relationships, not just those with media coverage. Accordingly, I use a size-adjustment procedure for each variable that allows me to sort on each characteristic individually without inadvertently sorting on the other characteristics.

The size adjustment procedure for illiquidity, PIN, analyst coverage, institutional ownership, newswire messages, and word length mirrors the size adjustment procedure for media coverage described earlier. Taking the illiquidity variable as an example, a firm's size-adjusted illiquidity is the firm's illiquidity quintile ranking within its size quintile on day *t*. The other size-adjusted variables are defined analogously, except for the analyst coverage and institutional ownership adjustments. To ensure that the results are economically meaningful and do not result from database omissions, I restrict the sample to firms with positive values of $AnalystsSA_{it}$ and positive values of $InstOwnSA_{it}$ before generating the quintile rankings for analyst coverage and institutional holdings, respectively. That is, the bottom quintiles contain firms with low analyst coverage and low institutional holdings, and exclude firms with no coverage and no holdings.[5] I use firm size and the six size-adjusted variables in the regression subsamples reported in Table 3.

[Insert Table 3 here.]

For brevity, Table 3 reports only the regression coefficients of primary interest, which are $Turn_{it}*Ret_{it}$, $news_{it}*Turn_{it}*Ret_{it}$, and $news_{it}* Ret_{it}$, and only the results within the top and bottom quintiles of each characteristic sort. The first set of three columns examines these three coefficients in the top characteristic quintile, the next set looks at the bottom quintile, and the last set of three columns computes the difference in the three coefficients across the quintiles.

The last two rows of columns three and six in Table 3 show that the $news_{it}*Ret_{it}$ coefficient depends critically on the number of wire messages on a news day ($MsgSA_{it,}$). The impact of news on reversal of day-0 firm returns is five times higher when day-0 firm news appears in many distinct newswire messages (i.e., 9.5% versus 1.9%), which is a statistically significant difference at the 1% level. This result is consistent with the interpretation that stories

[5] The results are similar if I include the firms with no analyst coverage and no institutional holdings, but these groups of firms often have very few news stories.

with many wire messages are more informative than other stories. Several market microstructure models, including the one in Section I, predict that market reactions to these informative stories would positively predict post-news returns, which is consistent with the results in Table 3.

More generally, columns three and six in Table 3 show that the $news_{it}$*Ret_{it} coefficient remains positive, statistically significant, and economically significant in all 12 (six by two) firm and news characteristic quintiles. The magnitude of the coefficient varies substantially with firm size (from 2.4% to 4.8% of daily returns), but there is no significant variation across the four size-adjusted firm characteristics. The last column in Table 3 shows that the difference in the $news_{it}$*Ret_{it} coefficient values across the top and bottom size quintiles is significant at the 5% level. This suggests that a typical news story conveys more value-relevant information for small firms, perhaps because more alternative sources of information exist for large firms.

The impact of news on volume-induced return momentum ($news_{it}$*$Turn_{it}$*Ret_{it}) is positive and statistically significant at the 5% level in nine of the ten firm characteristic quintile regressions, including the top size quintile—see the first five rows of columns two and five in Table 3. The lone exception is the regression with the most liquid firms, where the coefficient is insignificantly positive. For the firms in the bottom size and top illiquidity quintiles, the coefficients on $news_{it}$*$Turn_{it}$*Ret_{it} are so large that volume-induced momentum on news days overwhelms the volume-induced reversal on a typical day (negative $Turn_{it}$*Ret_{it} coefficients). This suggests that news plays an especially important role for small firms and illiquid firms. Furthermore, the impact of news on volume-induced reversal (i.e., the $news_{it}$*$Turn_{it}$*Ret_{it} coefficient) differs significantly by illiquidity. Interpreting this finding in the context of the model in Section I, it is consistent with the joint hypothesis that stock illiquidity is a proxy for information asymmetry, trading volume is a proxy for liquidity provision, and a key role of public news is to resolve information asymmetry. Conversely, if one interprets large returns on high-volume news days as resolving information asymmetry, the results in Table 3 validate illiquidity as a proxy for the presence of asymmetric information.

Interestingly, the last row in columns two and five of Table 3 shows that there is little difference in return momentum for high- and low-volume news days if one controls for a key characteristic of the news itself: the number of newswire messages ($MsgSA_{it}$,). This suggests that the role of news-day volume is to distinguish between informative and uninformative news stories; and that the more direct measure of news informativeness partly subsumes this role.

To further scrutinize this result, I add the newswire messages variable ($msgSA_{it}$,) and an interaction term with returns ($msgSA_{it}*Ret_{it}$) to the original regression specification in equation (6). I demean the newswire message variable by firm size quintile and trading day to create a size-adjusted variable ($msgSA_{it}$) with a zero mean. The interaction term with abnormal returns is defined as $msgSA_{it}*Ret_{it}$. To include these two variables in the regressions, I define them to be zero on all non-news days. This convention does not materially change the coefficients on these variables or the interaction terms from the estimates that one would obtain using only news days. The full regression specification in equation (7) is the same as equation (6) with two extra terms:

$$Ret_{i,t+2,t+10} = a + b_1 * Ret_{it} + b_2 * news_{it}*Ret_{it} + b_3 * Turn_{it}*Ret_{it} + b_4 * news_{it}*Turn_{it}*Ret_{it} + d_1\ msgSA_{it}*Ret_{it} + d_2\ msgSA_{it} + c * Controls_{it} + e_{it} \text{ for all } i \text{ on each day } t \quad (7)$$

Table 4 displays the coefficient estimates on the two message variables, along with the coefficients on the key news and reversal terms.[6] The main result is that the coefficients on the new interaction term ($msgSA_{it}*Ret_{it}$) has the expected signs, and is highly statistically significant in all specifications. That is, news stories consisting of more wire messages are better predictors of reduced return reversal. For a two-standard-deviation increase in newswire messages (+1.22),

[6] The coefficients on the control variables that are not shown change by very little in these specifications.

the estimates in column one show that return reversal decreases by 3.4% of daily returns. This magnitude is comparable to the magnitude of unconditional return reversal for news days (6.4% of daily returns). The other columns in Table 4 show that the estimates remain robust regardless of the regression specification and time period. In summary, the news stories with the most informative characteristics are the most powerful predictors of lower return reversal. This is consistent with the models in Section I, Kim and Verrecchia (1991), Wang (1994), Holden and Subrahmanyam (2002), and LMSW (2002). It also supports the view that the public news indicator variable is a noisy proxy for public information arrival.

[Insert Table 4 here.]

The differences between the consistently positive and significant coefficients on $news_{it}*Turn_{it}*Ret_{it}$ in Table 4 and the trivial and insignificant coefficients on $news_{it}*Turn_{it}*Ret_{it}$ in the last two rows of Table 3 is noteworthy. The Table 4 regressions include all news stories across all news characteristic quintiles. In these regressions, although the coefficient on $news_{it}*Turn_{it}*Ret_{it}$ (0.0094) is only half the magnitude of the original Table 1 coefficient (0.0188), news-day volume retains significant predictive ability for future returns. The Table 3 regressions include subsets of news stories within the same newswire message quintile. In these subsample regressions, variation in news-day volume does not seem to predict returns. This suggests that the number of newswire messages subsumes much, but not all, of the informational role of volume. From a theoretical perspective, trading volume accompanying the release of information is just a proxy for the resolution of information asymmetry. If one could accurately measure the informational content of the public signal, trading volume would play no role.

In summary, news on day 0 predicts a lower reversal of the day-0 return in days 2 to 10; and high-volume news predicts an even lower reversal of the day-0 return in days 2 to 10. The first result suggests that the informational role of news dominates any link between news and liquidity shocks.[7] The second result is consistent with the idea that volume that accompanies news is more likely to result from asymmetric information than asymmetric liquidity shocks.

IV. The Contemporaneous Relationship between Order Flows, Returns, and News

Here I explore possible mechanisms for why news-day returns predict post-news returns. The theoretical model in Section I, along with the several other models such as Wang (1994) and LMSW (2002), makes two predictions concerning the contemporaneous relationship between returns and order flows: 1) the correlation between absolute returns and volume temporarily increases while information asymmetry is being resolved; and 2) the price impact of informed order flow temporarily decreases while information asymmetry is low. I test these two predictions using an approach similar to an event study around news events.

A. Correlations between Absolute Returns and Trading Volume around News

I measure the contemporaneous association between absolute returns and volume using the simple univariate regression in equation (8):

$$Turn_{it} = Intercept + Slope * |Ret_{it}| + e_{it} \text{ for all } i, t, \tag{8}$$

The goal of this regression is not to assert causality, but to measure the association between absolute returns and volume. Switching the independent and dependent variables does not change their underlying correlation. Because the theoretical prediction is that the total correlation between absolute returns and volume increases as information asymmetry is resolved, equation

[7] This inference receives further support from the results in Engelberg (2008) and Tetlock et al. (2008). These papers show that negative words contained in news stories convey negative information about firms' cash flows.

(8) omits other contemporaneously measured variables. However, in a realistic empirical setting, variables aside from information asymmetry could affect the correlation between volume and absolute returns. To control for these variables, I examine *changes* in the volume-absolute return correlation before and after the same news events—i.e., in event time. Including other variables in equation (8) affects the magnitude of the partial correlation between volume and absolute returns, but does not affect the qualitative results below.

[Insert Table 5 here.]

Table 5 reports the details of the estimates of equation (8) using daily cross-sectional regressions. The parentheses below the coefficients contain Newey-West (1987) standard errors that allow for autocorrelation of up to three daily lags in the time series of coefficients. The daily regressions in equation (8) are not based on observations with overlapping time intervals because all variables are measured on the same trading day. Table 5 reports the average slope, intercept, R^2, and correlation coefficients for these daily regressions. The five columns denote five different subsamples in which I estimate equation (8): all days, days with news, days without news, days with earnings-related news, and days with non-earnings news. Not surprisingly, in all subsamples, there is a strong positive relationship between absolute returns and trading volume. More interestingly, the R^2 of the regression increases from just 6.0% on non-news days, to 17.2% on non-earnings news days, and to 36.6% on earnings news days, suggesting that the correlation between absolute returns and volume is related to the informativeness of public news events.

In unreported results, I compute the monthly average of the daily correlation between absolute returns and abnormal turnover on days with news and days without news, and the difference between these two correlations. This analysis shows that the differences in the average correlation coefficients between news and non-news days are positive for all 342 months in the sample. The news correlation consistently exceeds the non-news correlation in the post-1997 period, indicating that survivorship bias in the pre-1997 period is not driving the results.

Of course, the firms in the news and no-news subsamples are quite different in terms of size, volatility, turnover, and other dimensions that could affect the correlation between absolute returns and volume. Therefore, I use an event-study approach to create a “no-news” group of firms with the same firm composition as the news group. I estimate equation (8) in 21 different subsamples that include absolute returns and abnormal turnover for all firms with news exactly k days ago, where k is an integer ranging from -10 to +10 days relative to the news event. This produces a cross-sectional correlation between absolute returns and volume for each k value.

Figure 3 reports the correlation coefficients from these 21 regressions. The correlation between absolute returns and volume rises rapidly before a public news event, and declines rapidly after a news event occurs. Figure 3 shows how the cross-sectional relationship in Table 5 changes over time, before and after a news event.

[Insert Figure 3 here.]

There are at least two possible reasons why the correlation between absolute returns and abnormal turnover is higher on days with news stories. The microstructure explanation in the model in Section I and related models is that relatively uninformed traders learn about expected returns when news resolves information asymmetry. These traders buy when they learn that expected returns are high. An alternative explanation for the correlation between absolute returns and volume is that investors are more likely to trade a stock when an event draws their attention to the stock market. In fact, Barber and Odean (2008) show that individual investors are more likely to *buy* the stocks of firms that experience extreme abnormal return events and firms that are in the news. This aggressive buying activity could increase volume on days with extreme returns, particularly if news accompanies extreme returns.

To investigate the plausibility of the stories based on microstructure models and Barber and Odean's (2008) behavioral finding, I estimate equation (8) for news days, pre-news days, and post-news days within subsamples sorted by firm characteristics. I use k = -10 and +10 as the pre-news and post-news days—other values of k give similar results. Panel A in Table 6 reports the volume-absolute return correlation from subsamples sorted by several news event characteristics: all news, no news, earnings news, no earnings news, and high and low newswire messages ($MsgSA_{it}$). Panel B in Table 6 reports the correlations for subsamples sorted by the firm characteristics used earlier: size, analyst coverage, PIN, institutional ownership, and illiquidity.

For the top and bottom quintile of illiquidity, the table also reports the correlation from three subsamples sorted by the number of days elapsed (k = -10, 0, or +10) since a non-news event occurred. This allows for a difference-in-difference-in-difference comparison of the post-news and post-non-news change in correlations between liquid and illiquid stocks. The third difference is an effective control for possible differences in the mean reversion of pre-news liquidity in liquid and illiquid stocks if one assumes that mean reversion in liquidity affects both the post-news and post-non-news changes in correlations equally. The microstructure models predict that the correlation between absolute returns and volume should decline by more after news that resolves more asymmetric information. By contrast, the attention-based mechanism should be strongest for stocks with the highest individual and lowest institutional ownership.

[Insert Table 6 here.]

The post-news differences in correlations displayed in Table 6 generally support the information asymmetry explanation. For example, LMSW (2002) argue that asymmetric information is more prevalent in small stocks and illiquid stocks. Row three in Panel B in Table 6 indicates that the post-news decline in the correlation between absolute returns and volume is significantly larger (by 0.119) for stocks in the bottom size quintile than for stocks in the top quintile. Similarly, row 15 in Panel B shows that correlations decline by more for stocks in the top size-adjusted liquidity quintile than for stocks in the bottom quintile (by 0.018). The last (DDiff) row in Panel B shows that controlling for differences in the mean reversion of liquidity makes this decline appear even larger (0.034). These results are consistent with the idea that news plays a greater role in resolving information asymmetry for small stocks and illiquid stocks. The evidence on the number of newswires ($MsgSA_{it}$) in the last three rows in Panel A of Table 6 also suggests that news accompanies the release of asymmetric information. The decline in correlation between absolute returns and volume (from 0.616 to 0.302) is especially large in the ten days after news stories consisting of many wire messages.

Table 6 offers less support for the attention-based story, but one cannot rule it out altogether. Contrary to the attention-based story, the impact of news on the correlation between absolute returns and volume is larger in stocks with high institutional (not individual) ownership. One possible explanation is that information asymmetry is higher in these stocks. The empirical results from sorting the sample by PIN and analyst coverage are insignificant. Theoretically, these variables are difficult to interpret in light of the two competing theories. Although high PIN stocks presumably have higher information asymmetry, they could also have fewer individual investors with behavioral biases. Similarly, the mixed results for analyst coverage could stem from two offsetting effects: higher information asymmetry for stocks with low analyst coverage, but less attention for stocks with low coverage. Overall, the evidence for this particular attention-based mechanism is somewhat weak.

B. The Price Impact of Order Flow around News

The microstructure model in Section I predicts that price impact of trading should temporarily decline around news events if news resolves asymmetric information. I test this theory using event tests similar to those in the previous subsection. To obtain a noisy proxy for the price impact of informed trading, I assume that informed signed order flow is positively correlated with total signed order flow. I use the Lee and Ready (1991) algorithm to sign total order flow in the ISSM and TAQ databases. The definition of price impact is the ratio of the covariance of total signed order flow and returns to the variance of total signed order flows, which is equivalent to a univariate regression coefficient of returns on total signed order flows. For each firm on each trading day, I compute this covariance and variance using 5-minute intervals to aggregate signed order flows and returns. Because informed traders may trade in larger quantities than uninformed traders (e.g., Barber, Odean, and Zhu (2009)), I measure total signed order flows using the number of shares in each transaction, rather than the number of transactions or dollar-weighted transaction amounts. The share-weighted price impact measure is equal to the percentage price impact of transacting one percent of the firm's total shares outstanding, which matches the theoretical construct in the model in Section I.

I measure the cross-sectional average of price impact for all firms 10 days before, during, and 10 days after they experience news events. Panel A in Table 7 reports these averages within subsamples sorted by several news event characteristics: all news, no news, earnings news, no earnings news, and high and low newswire messages ($MsgSA_{it}$). Panel B shows price impacts around news events sorted by firm characteristics: size, analyst coverage, PIN, institutional ownership, and illiquidity. In the top and bottom quintile of each characteristic, the table reports the average price impact from three subsamples sorted by the number of days elapsed (k = -10, 0, or +10) since a news event occurred. For the top and bottom quintile of illiquidity, the table also reports the average price impact from three subsamples sorted by the number of days (k = -10, 0, or +10) since a non-news event occurred. As before, this comparison of the post-news and post-non-news change in price impact in liquid and illiquid stocks adjusts for possible differences in the mean reversion of pre-news liquidity in liquid and illiquid stocks.

[Insert Table 7 here.]

I infer the magnitude of the temporary decline in price impact around news by measuring the post-news increase in price impact. Panel A in Table 7 reports that the average drop in price impact around news is economically and statistically significant: starting from an impact of 1.67% prior to the news, to 1.58% on the news day, and to 1.65% after the news. A difference of 0.07% implies that a buyer-initiated trade of 1% of a firm's shares outstanding results in a 0.07% higher firm stock price. This increase of 0.07% is 4.5% of the 1.58% price impact on a news day. If the correlation between informed trading and total signed order flows is much less than one, this 4.5% change in price impact greatly underestimates the economic effect of public news.

[Insert Figure 4 here.]

To examine the time horizon of the price impact effect, I compute price impact in each of the ten days before and after news events. Figure 4 displays the result of this analysis. Price impact after news is materially lower than price impact before news at horizons of at least three trading days. For example, impact on day $t - 2$ is 1.66%, whereas impact on day $t + 2$ is 1.60%. This 0.06% decrease is statistically significant at the 5% level. Comparing price impact ten days before and after news, however, there is a decrease of just 0.02%, which is insignificant at the 5% level—see column six in Table 7.

Table 7 also allows for comparisons of the post-news increase in price impact across news events and firms with different characteristics. The sixth and ninth rows in Panel A show that the post-news increase in price impact is much higher for newswires that mention firm earnings and that occur in multiple messages. The last row in Panel B in Table 7 shows that firms with illiquid stocks experience a 0.18% higher post-news change in price impact than firms with liquid stocks. These three results are consistent with the idea that a key role of news is to resolve information asymmetry: earnings news and news with multiple wire messages is likely to be particularly informative; and pre-news information asymmetry is likely to be higher in illiquid stocks. There are no significant differences in the other characteristic sorts in Panel B.

V. Concluding Discussion

The four main results are that public news predicts substantially lower ten-day reversals of daily stock returns, higher ten-day volume-induced momentum in daily returns, lower correlations between absolute returns and volume, and higher price impacts. One can interpret these facts in the context of recent microstructure models. The negative impact of news on return reversals suggests that news accompanies the revelation of information more often than it accompanies liquidity shocks. The positive impact of news on volume-induced return momentum suggests that news resolves asymmetrically held information. Cross-sectional variation in this finding suggests news resolves more asymmetric information in illiquid stocks. The temporary increase in the correlation between absolute returns and volume during news, particularly earnings news, provides further support for the asymmetric information story. The increase in this correlation is again larger in illiquid stocks and in small stocks, where information asymmetry is likely to be high. Similarly, the temporary decrease in price impact during news suggests that news resolves information asymmetry, particularly in illiquid stocks.

Depending on the news-day volume, the predictive power of news for return reversals ranges from 17 bps to 33 bps over a nine-day span. These magnitudes could represent part of the compensation for the uninformed traders who provide liquidity to informed traders in the model in Section I and in the Kim and Verrecchia (1991), Wang (1994), Holden and Subrahmanyam (2002), and LMSW (2002) models. In this interpretation, good public news reveals that future cash flows are high and that past liquidity shocks to informed traders were low. There are at least two explanations for why prices rapidly increase in a two-week span following this good news, rather than increasing gradually as the stock pays dividends. One possibility is that the negative liquidity shocks experienced by informed traders' dissipate in the two weeks after the news, which would alleviate negative price pressure. A second possibility is that uninformed traders supply liquidity gradually over the next two weeks, rather than acting instantly after the news.

The findings here show that public information plays a key role in informing a subset of investors. This could help explain why Roll (1988) and others find that public news cannot, by itself, account for a substantial portion of asset return volatility. If some investors have already acted on the information released in the news, news will have a muted impact on prices.

Nevertheless, the resolution of asymmetric information through news is associated with trading volume; and this news-day volume, in combination with news-day returns, predicts future returns. Somewhat surprisingly, the number of newswire messages subsumes much of the predictive power of news-day trading volume. The ability to predict future returns using such crude measures of informational content is encouraging for future research on public news.

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Table 1: The Impact of News on Return Reversal and Volume-Induced Return Momentum

Table 1 reports all of the estimated coefficients from the regression in equation (6):

$$Ret_{i,t+2,t+10} = a + b_1 * Ret_{it} + b_2 * news_{it}*Ret_{it} + b_3 * Turn_{it}*Ret_{it} + b_4 * news_{it}*Turn_{it}*Ret_{it} + c * Controls_{it} + e_{it} \text{ for all } i \text{ on day } t \quad (6)$$

where $Controls_{it} = [News_{it}\ size_{it}*Ret_{it}\ news_{it}*Turn_{it}\ Turn_{it}\ Size_{it}\ BM_{it}\ Mom_{it}\ TVol_{it}]^T$. The dependent variable ($Ret_{i,t+2,t+10}$) is the firm's raw return from day $t+2$ to $t+10$. The independent variables include day-t market-adjusted returns (Ret_{it}), the news indicator ($News_{it}$), abnormal turnover ($Turn_{it}$), interactions between news and returns ($news_{it}*Ret_{it}$), turnover and returns ($Turn_{it}*Ret_{it}$), news, turnover, and returns ($news_{it}*Turn_{it}*Ret_{it}$), firm size and returns ($size_{it}*Ret_{it}$), and news and turnover ($news_{it}*Turn_{it}$). Other controls include size ($Size_{it}$), book-to-market (BM_{it}), annual return momentum (Mom_{it}), and monthly return volatility ($TVol_{it}$). I estimate equation (6) daily using all firms much like Fama and MacBeth (1973). The point estimate is the time series average of the daily regression coefficients. The Newey-West (1987) standard errors in parentheses below are robust to autocorrelation up to 10 daily lags and heteroskedasticity in the daily coefficient estimates. The five columns denote subsamples used to estimate equation (6): all trading days, excluding non-earnings news, excluding earnings news, and pre- and post-1997. The * and ** symbols denote statistical significance at the 5% and 1% levels.

Independent Variable	All	No Non-Earn News	No Earn News	1979-1996	1997-2007
Ret_{it}	-0.098**	-0.084**	-0.100**	-0.125**	-0.067**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)
$news_{it}*Ret_{it}$	0.042**	0.084**	0.029**	0.038**	0.043**
	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)
$Turn_{it}*Ret_{it}$	0.0088**	0.0058**	0.0084**	0.0120**	0.0019
	(0.0012)	(0.0015)	(0.0012)	(0.0013)	(0.0024)
$news_{it}*Turn_{it}*Ret_{it}$	0.0188**	0.0091*	0.0174**	0.0172**	0.0193**
	(0.0030)	(0.0043)	(0.0035)	(0.0049)	(0.0036)
$size_{it}*Ret_{it}$	-0.0043**	-0.0005	-0.0051**	-0.0092**	-0.0025
	(0.0010)	(0.0012)	(0.0010)	(0.0012)	(0.0018)
$News_{it}$	-0.0001	-0.0005*	0.0000	0.0002	-0.0001
	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0001)
$news_{it}*Turn_{it}$	-0.0007**	-0.0005*	-0.0003*	-0.0007**	-0.0007**
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
$Turn_{it}$	0.0023**	0.0020**	0.0023**	0.0022**	0.0024**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
$Size_{it}$	-0.0003**	-0.0003	-0.0003**	-0.0003	-0.0004*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
BM_{it}	0.0018**	0.0020**	0.0019**	0.0019**	0.0018**
	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0006)
Mom_{it}	0.0066**	0.0060**	0.0067**	0.0078**	0.0055**
	(0.0007)	(0.0008)	(0.0007)	(0.0009)	(0.0011)
$TVol_{it}$	-0.115**	-0.099**	-0.115**	-0.132**	-0.101**
	(0.023)	(0.029)	(0.023)	(0.023)	(0.038)
Average R^2	0.047	0.045	0.047	0.047	0.047
Avg Obs per Day	2279	2271	2222	1900	2872
Days	7098	4432	7096	4335	2763

Table 2: Pairwise Correlations between Raw Firm and News Characteristics

Table 2 displays the average daily correlations between daily media coverage ($News_{it}$), quarterly media coverage ($News3Mo_{it}$), size ($Size_{it}$), illiquidity ($Illiquidity_{it}$), analyst coverage ($Analysts_{it}$), PIN (PIN_{it}), institutional ownership ($InstOwn_{it}$), and wire messages (Msg_{it}). The Newey-West (1987) standard errors in parentheses below are robust to autocorrelation up to 250 lags and heteroskedasticity in the daily correlation estimates. Daily media coverage ($News_{it}$) is a 0 or 1 indicator of whether firm *i* has news on day *t*. Quarterly media coverage ($News3Mo_{it}$) is the fraction of trading days in which a firm appears in the news during the three most recent calendar months. Illiquidity ($Illiquidity_{it}$) is the daily Amihud (2002) illiquidity measure averaged over trading day *t-4* through day *t*. The Amihud (2002) illiquidity measure on day *t* is given by $10^6 * |Ret_{it}| / (Volume_{it})$ where $Volume_{it}$ is the stock's dollar volume on day *t*. PIN is the firm's PIN in the previous calendar year as described in Easley, Hvidkjaer, O'Hara (2005). Analyst coverage ($Analysts_{it}$) is the number of analysts with yearly earnings forecasts for a stock in the previous calendar month. Wire messages (Msg_{it}) is the number of distinct DJ newswire messages for firm *i* on day *t*. Institutional ownership ($InstOwn_{it}$) is the sum of all institutional holdings divided by the firm's market capitalization at the end of each calendar quarter. Before computing the correlations, I add a constant and take the log of each raw variable with highly positive skewness. These raw variables and their associated constants are quarterly media coverage (0.95), monthly analyst coverage (0), weekly illiquidity (1), and wire messages (1).

	$News_{it}$	$News3Mo_{it}$	$Size_{it}$	$Illiquidity_{it}$	$Analysts_{it}$	PIN_{it}	$InstOwn_{it}$	Msg_{it}
$News3Mo_{it}$	0.390	1.000						
	(0.009)							
$Size_{it}$	0.231	0.519	1.000					
	(0.016)	(0.029)						
$Illiquidity_{it}$	-0.147	-0.342	-0.750	1.000				
	(0.009)	(0.016)	(0.010)					
$Analysts_{it}$	0.168	0.389	0.727	-0.629	1.000			
	(0.013)	(0.026)	(0.007)	(0.007)				
PIN_{it}	-0.140	-0.310	-0.578	0.499	-0.499	1.000		
	(0.011)	(0.021)	(0.015)	(0.018)	(0.016)			
$InstOwn_{it}$	0.090	0.220	0.452	-0.509	0.526	-0.209	1.000	
	(0.003)	(0.007)	(0.017)	(0.009)	(0.010)	(0.015)		
Msg_{it}		0.293	0.235	-0.129	0.154	-0.152	0.036	1.000
		(0.015)	(0.015)	(0.006)	(0.011)	(0.009)	(0.005)	

Table 3: The Impact of News on Reversal and Volume-Induced Momentum Sorted by Firm and News Characteristics

Table 3 reports the estimated coefficients (b_2, b_3, and b_4) on $news_{it}*Ret_{it}$, $Turn_{it}*Ret_{it}$, and $news_{it}*Turn_{it}*Ret_{it}$ from the regression (6):

$$Ret_{i,t+2,t+10} = a + b_1 * Ret_{it} + b_2 * news_{it}*Ret_{it} + b_3 * Turn_{it}*Ret_{it} + b_4 * news_{it}*Turn_{it}*Ret_{it} + c * Controls_{it} + e_{it} \text{ for all } i, \qquad (6)$$

where $Controls_{it} = [News_{it}\ size_{it}*Ret_{it}\ news_{it}*Turn_{it}\ Turn_{it}\ Size_{it}\ BM_{it}\ Mom_{it}\ TVol_{it}]^T$. The dependent variable ($Ret_{i,t+2,t+10}$) is the firm's raw return from day $t+2$ to $t+10$. The independent variables include day-t market-adjusted returns (Ret_{it}), the news indicator ($News_{it}$), daily abnormal turnover ($Turn_{it}$), interactions between news and returns ($news_{it}*Ret_{it}$), turnover and returns ($Turn_{it}*Ret_{it}$), news, turnover, and returns ($news_{it}*Turn_{it}*Ret_{it}$), firm size and returns ($size_{it}*Ret_{it}$), and news and turnover ($news_{it}*Turn_{it}$). Other controls include size ($Size_{it}$), book-to-market (BM_{it}), annual return momentum (Mom_{it}), and monthly return volatility ($TVol_{it}$). I estimate equation (6) daily using all firms much like Fama and MacBeth (1973). The full sample coefficient estimate is the time series average of the daily cross-sectional regression coefficients. The Newey-West (1987) standard errors in parentheses below are robust to autocorrelation up to 10 daily lags and heteroskedasticity in the daily coefficient estimates. The six rows denote six characteristics used to form subsamples in which I estimate equation (6). The characteristics are firm size ($Size_{it}$), and five size-adjusted characteristics: illiquidity ($IlliquiditySA_{it}$), analyst coverage ($AnalystsSA_{it}$), PIN ($PINSA_{it}$), institutional ownership ($InstOwnSA_{it}$), and newswire messages ($MsgSA_{it}$). The columns show the estimated $Turn_{it}*Ret_{it}$, $news_{it}*Turn_{it}*Ret_{it}$, and $news_{it}*Ret_{it}$ coefficients in the top characteristic-sorted quintile subsample, the bottom quintile subsample, and the difference in the coefficients between the top and bottom quintiles. The * and ** symbols denote statistical significance at the 5% and 1% levels.

	High Sort Variable			Low Sort Variable			High – Low Sort Variable		
Sort Variable	*TurnRet*	*newsTurnRet*	*newsRet*	*TurnRet*	*newsTurnRet*	*newsRet*	*TurnRet*	*newsTurnRet*	*newsRet*
$Size_{it}$	0.052**	0.024*	0.024**	-0.005*	0.019**	0.048**	0.048**	0.002	-0.027*
	(0.005)	(0.011)	(0.008)	(0.002)	(0.006)	(0.008)	(0.008)	(0.017)	(0.013)
$IlliquiditySA_{it}$	-0.014**	0.042**	0.038**	0.038**	0.015	0.036**	-0.047**	0.031**	-0.002
	(0.002)	(0.007)	(0.008)	(0.003)	(0.008)	(0.010)	(0.005)	(0.012)	(0.014)
$AnalystsSA_{it}$	0.010**	0.024**	0.036**	0.000	0.035**	0.042**	0.006	-0.012	-0.009
	(0.003)	(0.007)	(0.009)	(0.003)	(0.008)	(0.010)	(0.004)	(0.012)	(0.013)
$PINSA_{it}$	0.021**	0.019	0.054**	0.017**	0.055**	0.035**	0.005	-0.036	0.020
	(0.006)	(0.015)	(0.017)	(0.005)	(0.014)	(0.014)	(0.008)	(0.026)	(0.022)
$InstOwnSA_{it}$	0.010**	0.017**	0.043**	-0.005	0.022*	0.043**	0.012*	-0.006	-0.007
	(0.002)	(0.006)	(0.007)	(0.004)	(0.011)	(0.011)	(0.005)	(0.013)	(0.015)
$MsgSA_{it}$	0.003	0.004	0.095**	0.008**	0.007	0.019**	-0.001	-0.001	0.079**
	(0.002)	(0.004)	(0.008)	(0.001)	(0.005)	(0.005)	(0.001)	(0.001)	(0.010)

Table 4: The Impact of News Characteristics on Ten-Day ($Ret_{i,t+2,t+10}$) Return Reversals

Table 4 reports the estimated coefficients from the regression specification in equation (7):

$$Ret_{i,t+2,t+10} = a + b_1 * Ret_{it} + b_2 * news_{it}*Ret_{it} + b_3 * Turn_{it}*Ret_{it} + b_4 * news_{it}*Turn_{it}*Ret_{it} + d_1\ msgSA_{it}*Ret_{it} + d_2\ msgSA_{it} + c * Controls_{it} + e_{it} \text{ for all } i \text{ on each day } t \quad (7)$$

where $Controls_{it} = [News_{it}\ size_{it}*Ret_{it}\ news_{it}*Turn_{it}\ Turn_{it}\ Size_{it}\ BM_{it}\ Mom_{it}\ TVol_{it}]^T$. The return reversal, news-related reversal, message-related reversal, and word-length-related reversal coefficients (b_1, b_2, d_1 , and d_2) are the primary focus. The dependent variable ($Ret_{i,t+2,t+10}$) is the firm's raw return from day $t+2$ to $t+10$. The independent variables include day-t market-adjusted returns (Ret_{it}), the news indicator ($News_{it}$), interactions between news and returns ($news_{it}*Ret_{it}$), firm size and returns ($size_{it}*Ret_{it}$), turnover and returns ($Turn_{it}*Ret_{it}$), and news and turnover ($news_{it}*Turn_{it}$). The $msgSA_{it}$ variable is the log of the number of newswire messages for firm i on day t, adjusted for the average value for each size quintile. Other controls not shown include size ($Size_{it}$), book-to-market (BM_{it}), annual return momentum (Mom_{it}), monthly return volatility ($TVol_{it}$), and daily abnormal turnover ($Turn_{it}$). Lowercase variables denote demeaned variables. I estimate equation (7) daily using all firms much like Fama and MacBeth (1973). The coefficient estimate is the time series average of the daily cross-sectional regression coefficients. The Newey-West (1987) standard errors in parentheses below are robust to autocorrelation up to 10 daily lags and heteroskedasticity in the daily coefficient estimates. The three columns denote estimates equation (7) in three subsamples: all trading days, pre-1997, and post-1997. The * and ** symbols denote statistical significance at the 5% and 1% levels.

Independent Variable	All Days	1979-1996	1997-2007
Ret_{it}	-0.098**	-0.124**	-0.068**
	(0.003)	(0.003)	(0.005)
$news_{it}*Ret_{it}$	0.042**	0.035**	0.043**
	(0.004)	(0.008)	(0.004)
$msgSA_{it}*Ret_{it}$	0.028**	0.075**	0.027**
	(0.004)	(0.013)	(0.004)
$Turn_{it}*Ret_{it}$	0.0081**	0.0117**	0.0000
	(0.0012)	(0.0013)	(0.0025)
$news_{it}*Turn_{it}*Ret_{it}$	0.0100**	0.0105*	0.0099**
	(0.0032)	(0.0054)	(0.0038)
$News_{it}$	-0.0001	0.0002	-0.0002
	(0.0001)	(0.0002)	(0.0001)
$msgSA_{it}$	-0.0007**	-0.0006	-0.0007**
	(0.0001)	(0.0004)	(0.0001)
Average R^2	0.048	0.048	0.048
Avg Obs per Day	2280	1901	2873
Days	7082	4319	2763

Table 5: News and the Contemporaneous Volume-Absolute Return Correlation

Table 5 reports regression coefficients and correlation coefficients based on equation (8):

$$Turn_{it} = Intercept + Slope * |Ret_{it}| + e_{it} \text{ for all } i \text{ on each day } t, \qquad (8)$$

The dependent variable is abnormal daily turnover ($Turn_{it}$); and the independent variable is absolute daily returns $|Ret_{it}|$. To control for variables aside from information asymmetry that could affect the correlation between absolute returns and volume, I examine *changes* in the correlation before and after the same news events in Panel B. I estimate equation (8) using daily cross-sectional regressions. In parentheses, I report Newey-West (1987) standard errors that allow for autocorrelation of up to three daily lags in the time series of coefficients. Panel A in Table 5 reports the average slope, intercept, R^2, and correlation coefficients for these monthly regressions. The five columns denote five different subsamples in which I estimate equation (8): all days, days with news, days without news, days with non-earnings-related news, and days with earnings-related news. The * and ** symbols denote statistical significance at the 5% and 1% levels. To avoid clutter, I suppress all asterisks for the raw correlations.

Independent Variable	All	News	No News	Non-Earnings News	Earnings News
$\|Ret_{it}\|$	11.9**	14.4**	11.3**	13.0**	13.9**
	(0.07)	(0.11)	(0.08)	(0.12)	(0.14)
Constant	-0.205**	-0.068**	-0.215**	-0.080**	0.078**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Average R^2	0.079	0.212	0.060	0.172	0.366
Avg Obs per Day	2532	315	2217	381	93
Days	7132	7132	7132	4434	4434

Table 6: Volume-Absolute Return Correlation Sorted by Firm and News Characteristics

Table 6 reports only the correlation coefficients based on equation (8):

$$Turn_{it} = Intercept + Slope * |Ret_{it}| + e_{it} \text{ for all } i \text{ on each day } t, \qquad (8)$$

The dependent variable is abnormal daily turnover ($Turn_{it}$); and the independent variable is absolute daily returns $|Ret_{it}|$. The first three columns indicate the correlation between absolute returns and volume ten days prior to news (*t–10*), on the day of news (*t*), and ten days after news (t+*10*). I examine *changes* in the correlation between absolute returns and volume before and after the same news events in the last two columns. I obtain these estimates from regressions of equation (8) in three different subsamples that include absolute returns and volume for firms with news events exactly *k* days ago, where *k* is equal to either -10, 0, or +10 days relative to the news event. The post-event difference is the correlation on day *t+10* minus the correlation on day *t*, whereas the pre-post event difference is the correlation on day *t+10* minus the correlation on day *t–10*. I estimate equation (8) using daily cross-sectional regressions. In parentheses, I report Newey-West (1987) standard errors that allow for autocorrelation of up to three daily lags in the time series of coefficients. The rows in the two panels indicate the news or firm characteristic subsample in which I estimate the correlation between absolute returns and volume. Panel A compares news days versus non-news days, earnings news days versus non-earnings news days, and news days with newswire messages in the top versus bottom quintile. Panel B compares the top and bottom quintiles of size, analyst coverage, PIN, institutional ownership, and illiquidity. The last seven rows analyze correlations around no-news events in both illiquidity quintiles and the difference in difference (DDiff) in correlations between the two liquidity quintiles for news and non-news events. The * and ** symbols denote statistical significance at the 5% and 1% levels. To avoid clutter, I suppress all asterisks for the raw correlations.

Panel A: Correlations Between $Turn_{it+k}$ and $|Ret_{it+k}|$ on Day *t+k* Sorted by Type of News on Day *t*

Characteristic	Rank	Day *t–10* Correlation	Day *t* Correlation	Day *t+10* Correlation	Post-Event Difference	Pre-Post Event Difference
News on Day *t*	All	0.298	0.441	0.288	-0.153**	-0.010**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
No News on Day *t*	All	0.269	0.239	0.271	0.032**	0.002**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
	Diff				-0.185**	-0.012**
					(0.002)	(0.002)
Earnings News on Day *t*	All	0.298	0.583	0.295	-0.290**	-0.004
		(0.004)	(0.003)	(0.011)	(0.005)	(0.005)
Non-Earnings News on *t*	All	0.299	0.395	0.288	-0.107**	-0.011**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	Diff				-0.201**	0.009
					(0.005)	(0.006)
$MsgSA_{it}$	High	0.335	0.616	0.302	-0.315**	-0.034**
(News on Day *t*)		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
	Low	0.291	0.359	0.284	-0.075**	-0.007**
		(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
	Diff				-0.302**	-0.025**
					(0.005)	(0.005)

Panel B: Correlations Between $Turn_{it+k}$ and $\|Ret_{it+k}\|$ on Day $t+k$ Sorted by Firm Characteristic on Day t						
Characteristic	Rank	Day $t–10$ Correlation	Day t Correlation	Day $t+10$ Correlation	Post-Event Difference	Pre-Post Event Difference
$Size_{it}$	High	0.325	0.399	0.317	-0.083**	-0.009**
(News on Day t)		(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
	Low	0.302	0.447	0.280	-0.166**	-0.021**
		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
	Diff				0.119**	0.015**
					(0.004)	(0.005)
$AnalystsSA_{it}$	High	0.337	0.490	0.319	-0.171**	-0.018**
(News on Day t)		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
	Low	0.282	0.435	0.276	-0.159**	-0.007
		(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
	Diff				-0.008	-0.012
					(0.005)	(0.006)
$PINSA_{it}$	High	0.280	0.409	0.273	-0.136**	-0.006
(News on Day t)		(0.005)	(0.004)	(0.005)	(0.006)	(0.007)
	Low	0.270	0.421	0.267	-0.154**	-0.004
		(0.005)	(0.003)	(0.004)	(0.005)	(0.006)
	Diff				-0.003	-0.001
					(0.008)	(0.008)
$InstOwnSA_{it}$	High	0.303	0.466	0.288	-0.178**	-0.015**
(News on Day t)		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
	Low	0.297	0.421	0.279	-0.142**	-0.020**
		(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
	Diff				-0.027**	0.000
					(0.005)	(0.006)
$IlliquiditySA_{it}$	High	0.212	0.392	0.231	-0.161**	0.018**
(News on Day t)		(0.004)	(0.003)	(0.004)	(0.007)	(0.006)
	Low	0.361	0.493	0.327	-0.166**	-0.034**
		(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
	Diff				-0.018**	0.054**
					(0.005)	(0.006)
$IlliquiditySA_{it}$	High	0.195	0.177	0.222	0.045**	0.028**
(No News on t)		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Low	0.353	0.326	0.329	0.003	-0.024**
		(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
	Diff				0.042**	0.052**
					(0.002)	(0.001)
$IlliquiditySA_{it}$	DDiff				-0.034**	0.004
(News vs. None)					(0.006)	(0.006)

Table 7: Intra-Day Price Impact Sorted by Firm and News Characteristics

For firms and news events with different characteristics, Table 7 reports firms' average share-weighted price impact before, during, and after news and non-news events. Share-weighted price impact is based on total signed order flows and returns measured at 5-minute intra-day intervals. I use the Lee and Ready (1991) algorithm to sign total order flow in the ISSM and TAQ databases. Price impact is the ratio of the covariance of share-weighted signed order flow and returns to the variance of share-weighted signed order flows. The share-weighted price impact measure is equal to the percentage price impact of transacting one percent of the firm's total shares outstanding. The first three columns indicate the average price impact of order flow ten days prior to a firm event (*t–10*), on the event day (*t*), and ten days after the event (t+*10*). I examine *changes* in price impact before and after the events in the last two columns. In parentheses, I report Newey-West (1987) standard errors that allow for autocorrelation of up to three daily lags in the time series of average price impacts. The rows in the two panels indicate the news or firm characteristic subsample in which I estimate average price impact around news or non-news events. Panel A compares price impact on news days versus non-news days, earnings news days versus non-earnings news days, and news days with newswire messages in the top versus bottom quintile. Panel B compares price impact around news in the top and bottom quintiles of size, analyst coverage, PIN, institutional ownership, and illiquidity. The last seven rows analyze price impact around no-news events in both illiquidity quintiles and the difference in difference (DDiff) in correlations between the two liquidity quintiles for news and non-news events. The * and ** symbols denote statistical significance at the 5% and 1% levels. To avoid clutter, I suppress all asterisks for the raw price impacts.

Panel A: Average Price Impact on Day *t+k* Sorted by News Characteristic on Day *t*

Characteristic	Rank	Day *t–10* Price Impact	Day *t* Price Impact	Day *t+10* Price Impact	Post-Event Difference	Pre-Post Event Difference
News on Day *t*	All	1.67	1.58	1.65	0.07**	-0.02
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No News on Day *t*	All	1.76	1.77	1.76	-0.01**	0.00
		(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
	Diff				0.08**	-0.02
					(0.01)	(0.01)
Earnings News on Day *t*	All	1.74	1.53	1.68	0.15**	-0.06**
		(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Non-Earnings News on *t*	All	1.67	1.61	1.65	0.05**	-0.01
		(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	Diff				0.09**	-0.06**
					(0.02)	(0.02)
$MsgSA_{it}$	High	1.83	1.58	1.77	0.18**	-0.06**
(News on Day *t*)		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
	Low	1.63	1.58	1.62	0.04**	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Diff				0.13**	-0.05**
					(0.01)	(0.01)

Panel B: Average Price Impact on Day $t+k$ Sorted by Firm Characteristic on Day t						
Characteristic	Rank	Day $t–10$ Price Impact	Day t Price Impact	Day $t+10$ Price Impact	Post-Event Difference	Pre-Post Event Difference
$Size_{it}$	High	1.85	1.79	1.86	0.07**	0.01
(News on Day t)		(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
	Low	1.71	1.58	1.66	0.09**	-0.05*
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Diff				0.00	0.04
					(0.02)	(0.02)
$AnalystsSA_{it}$	High	1.67	1.60	1.67	0.07**	0.00
(News on Day t)		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Low	1.72	1.64	1.69	0.05*	-0.04
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Diff				0.03	0.03
					(0.02)	(0.02)
$PINSA_{it}$	High	1.94	1.81	1.96	0.15**	0.02
(News on Day t)		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
	Low	2.00	1.90	1.99	0.09**	-0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Diff				0.05	0.02
					(0.03)	(0.04)
$InstOwnSA_{it}$	High	1.19	1.10	1.15	0.05**	-0.04**
(News on Day t)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Low	2.55	2.46	2.57	0.11**	0.02
		(0.03)	(0.02)	(0.03)	(0.03)	(0.04)
	Diff				-0.04	-0.04
					(0.03)	(0.03)
$IlliquiditySA_{it}$	High	2.67	2.76	2.56	-0.19**	-0.11**
(News on Day t)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Low	1.55	1.38	1.54	0.16**	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Diff				-0.34**	-0.12**
					(0.04)	(0.03)
$IlliquiditySA_{it}$	High	3.08	3.39	3.01	-0.39**	-0.07**
(No News on t)		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
	Low	1.07	0.95	1.10	0.15**	0.03**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Diff				-0.52**	-0.10**
					(0.01)	(0.01)
$IlliquiditySA_{it}$	DDiff				0.18**	-0.03
(News vs. None)					(0.04)	(0.04)

Figure 1: Media Coverage across Firms and over Time

Figure 1 depicts how four media coverage measures change from 1979 to 2007. The bottom line is the monthly average of the daily fraction of sample eligible firms that have news in the DJ archive—see text for sample construction. The other three lines are three long-horizon coverage measures that include media coverage on trading days that meet the sample inclusion criteria. The top two lines represent the fraction of firms with at least one news story in the current month, and the fraction of firms with news in the most recent 12 months. The second line from the bottom is the fraction of trading days in the most recent 12 months that a firm appears in the news for the firm at the 90th percentile. This line represents news coverage for the most widely followed firms.

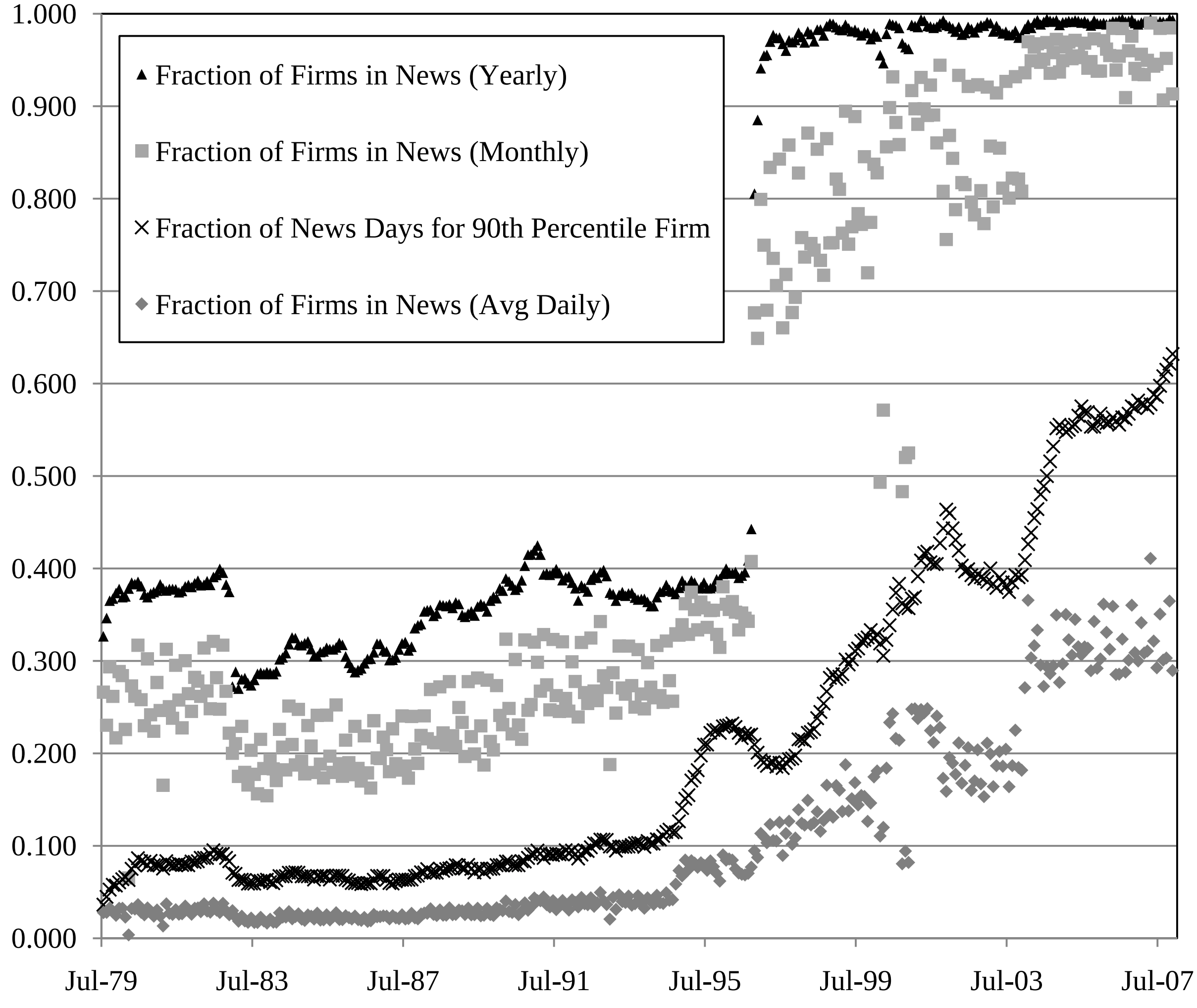

Figure 2: The Impact of News on Return Reversal and Volume-Induced Momentum

Figure 2 shows how the percentage reversal of a daily return depends on the news and trading volume observed on that day. The calculations in the figure come directly from the regression estimates of the four coefficients (b_1, b_2, b_3, and b_4) in equation (6):

$$Ret_{i,t+2,t+10} = a + b_1 * Ret_{it} + b_2 * news_{it}*Ret_{it} + b_3 * Turn_{it}*Ret_{it} + b_4 * news_{it}*Turn_{it}*Ret_{it} + c * Controls_{it} + e_{it} \text{ for all } i, t, \quad (6)$$

Table 1 reports these four coefficients on the variables Ret_{it}, $news_{it}*Ret_{it}$, $Turn_{it}*Ret_{it}$, and $news_{it}*Turn_{it}*Ret_{it}$. I compute the predicted value of the dependent variable when there is no news with high turnover, no news with low turnover, news with high turnover, and news with low turnover in the four sets of bars below. The value of $news_{it}$ is equal to either 0.702 or -0.099, depending on news or no news. For high or low turnover, the value of abnormal turnover is the 90th or 10th percentile of the turnover distribution conditional on news. The dark gray, light gray, and black bars denote three sets of coefficient estimates for the news- and volume-related return momentum in three subsamples: all trading days, excluding earnings news, and excluding non-earnings news. Columns one, two, and three in Table 1 report these coefficient values.

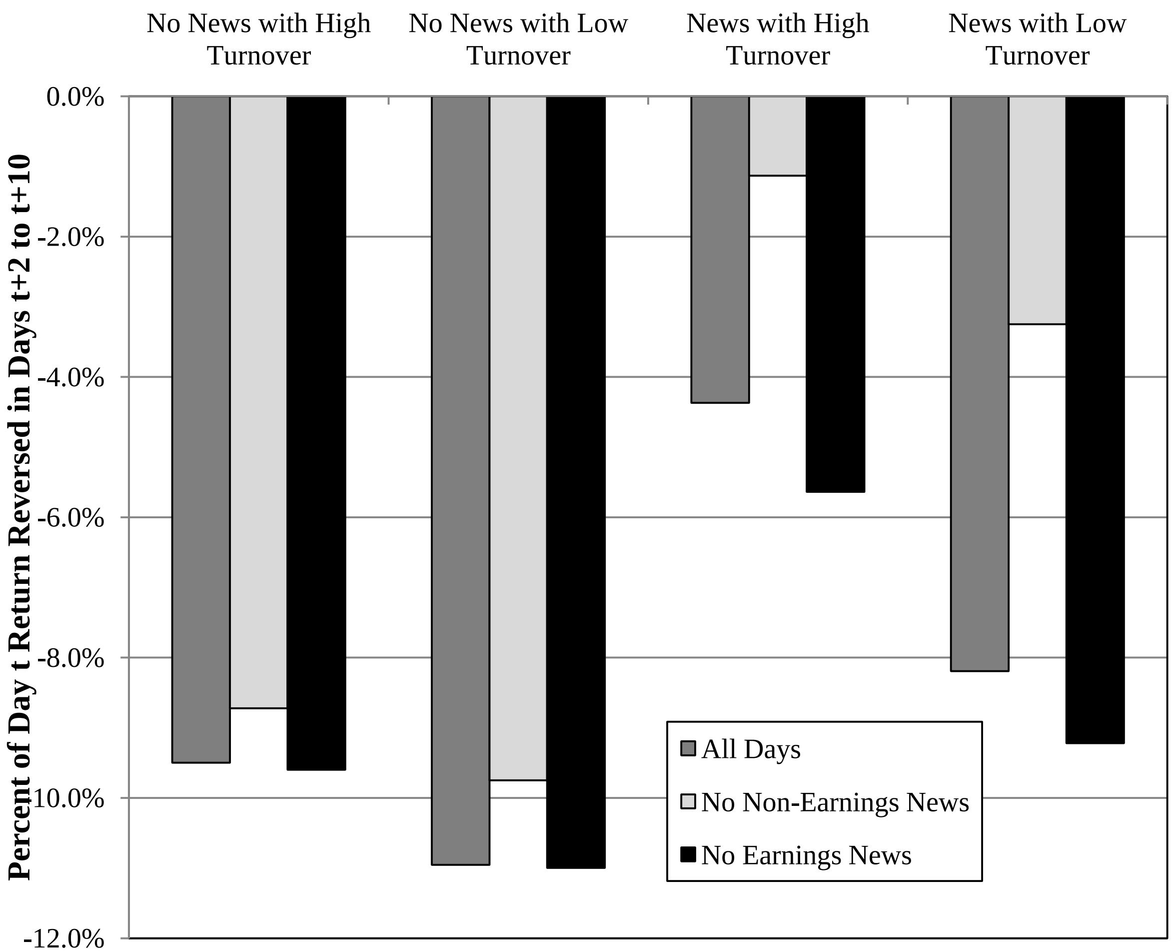

Figure 3: The Correlation between Absolute Returns and Volume around Public News

Figure 3 reports the correlation between absolute returns and abnormal turnover on 21 different days, ranging from 10 days before a news event occurs to 10 days after the event. The correlation coefficients come from daily cross-sectional regressions based on equation (8):

$$Turn_{it} = Intercept + Slope * |Ret_{it}| + e_{it} \text{ for all } i \text{ on day } t, \quad (8)$$

The independent variable is absolute daily returns $|Ret_{it}|$; and the dependent variable is abnormal daily turnover ($Turn_{it}$). To estimate the correlation between absolute returns and volume *k* days after a news event, I estimate equation (8) using only observations in which a firm experienced a news event *k* days ago. Repeating this procedure for integer values of *k* ranging from -10 to +10 generates the figure below. See Table 5 for further estimation details.

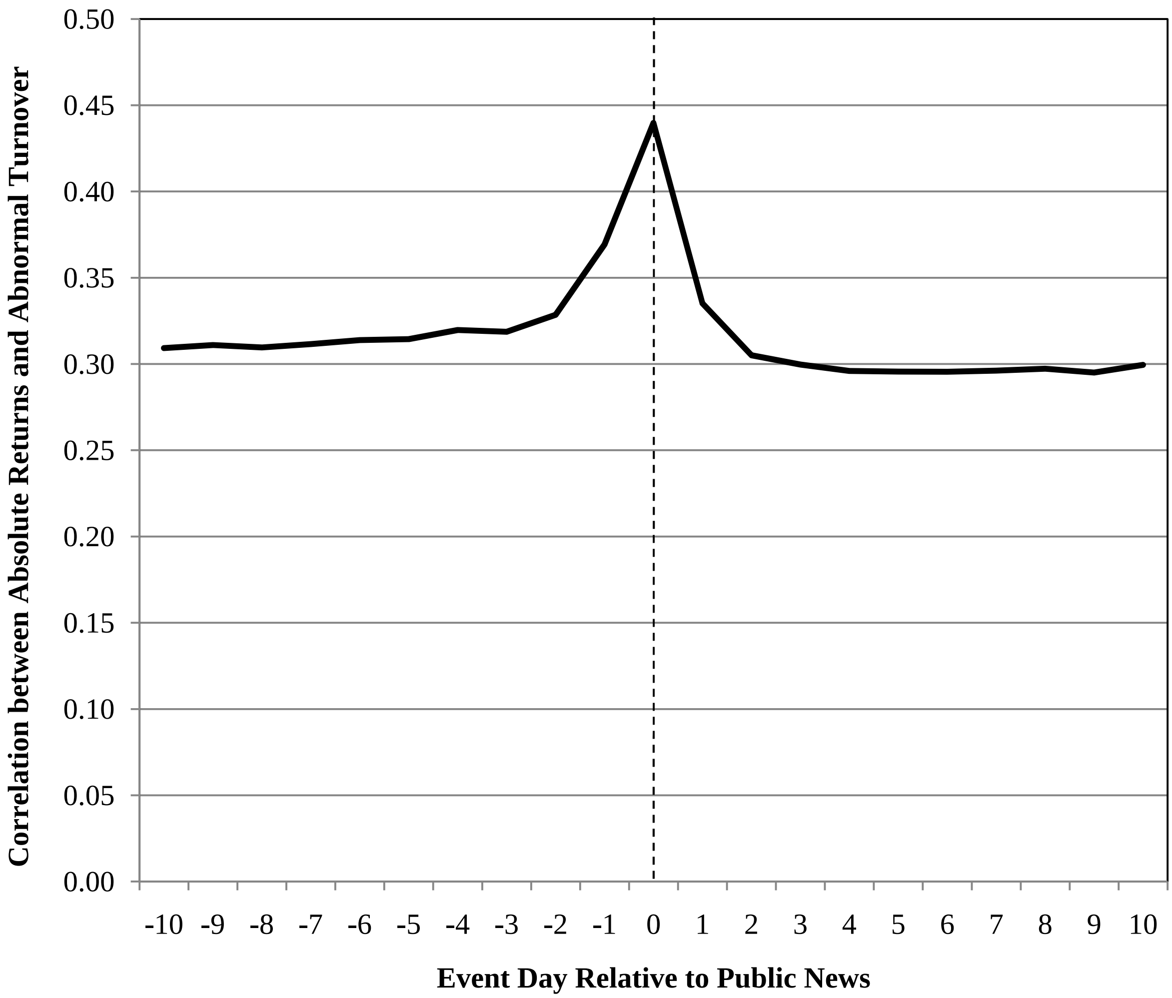

Figure 4: The Price Impact of Order Flow before and after Public News Events

For each of the ten days before and after firm news events, Figure 4 reports the daily price impact of signed order flow. I use the Lee and Ready (1991) algorithm to sign order flows as buyer-initiated or seller-initiated. To compute daily price impact, I aggregate order flows—as a percentage of shares outstanding—and calculate stock returns in each five-minute interval in a trading day. Price impact is the covariance of five-minute returns and five-minute order flows divided by the variance of five-minute order flows. This figure shows the cross-sectional average of price impact for all firms experiencing a news event *k* days ago, where *k* is an integer ranging from -10 to +10. See text for further estimation details.