Trading Without Public News:  
Another Look at the Intraday Volume-Volatility Stock Relations

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Abstract

This paper examines the intraday stock relations between trading volume and return volatility of large and small NYSE stocks in two partitioned samples, with and without identifiable public news. Data analysis suggests that return volatility is higher in the periods with public news, while trading volume is significantly higher in the no-news period, perhaps owing to the importance of private information for trading stocks. After necessary Bayesian adjustments to avoid large sample biases, we find bi-directional causality between volume and volatility, which supports the sequential information arrival hypothesis. For the period without public news, we find evidence that volume Granger-causes volatility without feedback. We argue that these results are broadly consistent with the overconfidence and biased self-attribution model of Daniel, Hirshleifer and Subrahmanyam (1998). Overconfident investors overestimate the precision of their private news signals and therefore trade too aggressively in the absence of public news; when public news arrives, investors’ biased self-attribution causes excessive volatility of returns.

JEL Codes: G12; G14

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1. Introduction

Research persists on the temporal relation between trading volume and return volatility of stocks. The mundane literature examines several alternative views of this relation, two of which are particularly interesting. First is the contention that volume and volatility are related contemporaneously, and the second view is that the two variables exhibit a causal (lead/lag) relation. The contemporaneous relation is based on the Mixture of Distribution Hypothesis (MDH) of Clark (1973), Harris (1987), among others. The MDH argues that the arrival of information impels simultaneous changes in volume and volatility to reach new market equilibrium. Thus, volume and volatility possess a contemporaneous correlation but not a lead-lag relation.

The causal relation between volume and volatility is predicted by the Sequential Information Arrival Hypothesis (SIAH) of Copeland (1976), Smirlock and Starks (1988) and others. The SIAH assumes that investors react to new information differently. Therefore, the formation of new market equilibriums is not instantaneous and requires some time (perhaps minutes), giving rise to a lead/lag relation between volume and volatility. Using intraday trading data for the 30 stocks in the DJIA, Darrat, Rahman, and Zhong (2003) recently report empirical results suggesting that high trading volume causes high return volatility, which is in accordance with the SIAH view but opposed to the MDH view.

Note that the SIAH assumes investors primarily react to news. However, financial markets often move dramatically in the absence of public news. In other words, stock prices appear too volatile to be justified by changes in fundamentals [Shiller (1981), Campbell and Shiller (1987), Zhong, Darrat and Anderson (2003)]. Excess volatility studies typically examine the link between news reported in the media and stock price movements, and conclude that investors overreact to unobserved stimuli [Roll (1988), and Mitchell and Mulherin (1994)]. If investors execute trades during periods without public news, then ‘excessive’ trading should be accompanied by subsequent return volatility. This phenomenon has nothing to do with the sequential information hypothesis (because there is no public
information available during the trading period), but it does imply that investors act on private signals or sentiments.

The types of Granger causality tests performed by Darrat, Rahman and Zhong (2003) cannot distinguish between SIAH and an alternative plausible hypothesis, the overconfidence hypothesis. The key difference between these two alternative hypotheses is whether public signals are present. The SIAH assumes that investors react rationally to the arrival of new public signals. In the absence of public signals, rational investors should not change their positions, and no causal link between volume and volatility should be observed. Conversely, the overconfidence hypothesis does not require the presence of public signals. Even without these signals, quasi-rational investors may still overreact to their own private signals and execute trading. Such trading without public signals can cause excessively high return volatility.

The main purpose of the paper is to re-examine the intraday lead-lag relation of volume and volatility in two perspectives: with and without identifiable public news. We propose several testable hypotheses for the intraday trading volume, return volatility, and for the causal relations between them. Separating the periods with and without public news and employing Bayesian adjustments to avoid large sample biases, we find consistent evidence that trading volume Granger-causes return volatility even during the periods without public news. These results provide support to the overconfidence hypothesis over the SIAH and suggest that investors trade according to their private signals and appear reluctant to close their positions afterwards.

This paper contributes to the volume-volatility literature in several ways. First, our data sampling procedure is carefully chosen for the empirical exercise. Fama (1998) argue that the anomaly literature is biased, focusing on events that show interesting results while ignoring other episodes that have no unusual patterns. Our analysis is free of this criticism. We are particularly interested in the intraday volume-volatility relation in periods without
identifiable public news. When testing the lead-lag relation in the news period, we do not focus on particular events but rather look at a wide range of news. As such, our data do not suffer from selection bias. Studies that take a similar data sampling approach in different directions include Pritamani and Singal (2001) and Chan (2003). Pritamani and Singal compile daily news stories for a subset of stocks from 1990 to 1992 and examine the return predictability following large price movements and information releases. Chan collects the news headlines for a sub-set of CRSP stocks over the period 1980-2000 and compares monthly returns following public news and returns after a similar price movement in the absence of public news. However, Holden and Subrahmanyam (2002) do not separate the news and no-news period in the empirical verification of their model for medium-term continuation (momentum) in asset returns.

Second, because the lead-lag relation between volume and volatility suggested by SIAH exists only in the presence of public signals, we test the SIAH using data that contain public news. Our results are supportive of the SIAH and find a bi-directional causality between volume and volatility in the news period.

Third, our results accord well with behavioral finance. In their overconfidence and biased self-attribution model, Daniel, Hirshleifer and Subrahmanyam (1998, DHS) argue that “stock prices overreact to private information signals and underreact to public signals” (DHS, p.1841). We provide a detailed discussion relating our results to the DHS hypothesis.

Finally, we distinguish between large-cap and smaller-cap stocks. We find that the volatilities of large stocks in the news period are significantly higher compared to the no-news period, whereas smaller stocks do not show material difference across the two periods. This evidence is consistent with the recent finding of Theobald and Yallup (2004) that large stocks react much quicker to price deviations from intrinsic values, and thus exhibit a more volatile price path compared to smaller stocks.
The remainder of the paper is organized as follows. Section 2 explains our methodology and data sampling procedure for testing the intraday volume-volatility relation in the news and no-news periods. Section 3 reports the empirical results. Section 4 discusses the implications of results and their relation to the DHS model of overconfidence and biased self-attribution behavior. Section 5 concludes the paper.

2. Research Design

2.1 volatility measures

We obtain estimates of the return volatility using an autoregressive conditional heteroskedasticity-based model. A typical characteristic of asset returns is volatility clustering where one period of high volatility is followed by more of the same and then successive periods of low volatility ensue [Bollerslev, Chou and Kroner (1992, 1994)]. Given this characteristic, the literature has witnessed a growing interest in generalized autoregressive conditional heteroskedasticity (GARCH) models that parameterize time-varying conditional variances of stochastic processes. Following Nelson (1991), we use the exponential version of GARCH (EGARCH) to measure return volatility for several reasons. Unlike GARCH, the EGARCH variant imposes no positive constraints on the estimated parameters and explicitly accounts for asymmetry common in asset return volatility, thereby avoiding possible misspecification in the volatility process [Glosten Jagannathan and Runkle (1993)]. In addition, EGARCH allows for a general probability density function (i.e., Generalized Error Distribution, GED), which nests the normal distribution along with several other possible densities. As Bollerslev, Chou and Kroner (1992) argue, imposing normality is baseless and could distort the estimates.

The EGARCH model expresses the conditional variance of a given time series as a non-linear function of its own past values and the past values of standardized innovations. We allow the squared root of the conditional variance to enter the mean return equation,
leading to an EGARCH-in-mean model (EGARCH-M). To allow for sufficient flexibility in the estimation, we use an ARMA (1,1) model for the conditional mean equation and specify the conditional variance as an EGARCH-M (1,1) process to ensure parsimonious estimations. The model can be written as:

\[ R_t = \psi + \alpha R_{t-1} + \beta \epsilon_t + \eta \sigma_t \]  

(1)

where the error term \( \epsilon_t \) is distributed as the generalized error distribution with a zero mean and a conditional variance \( \sigma_t^2 \) such that:

\[ \epsilon_t \sim GED(0, \sigma_t^2) \]  

(2)

\[ \sigma_t^2 = \exp \left\{ \phi \ln(\sigma_{t-1}^2) + \varphi \left[ \frac{\epsilon_t}{\sigma_{t-1}^2} - E \left( \frac{\epsilon_t}{\sigma_{t-1}^2} \right) \right] + \theta \left( \frac{\epsilon_t}{\sigma_{t-1}^2} \right) \right\} \]  

(3)

where \( R_t \) denotes stock returns, and \( \psi, \alpha, \beta, \eta, \phi, \gamma, \) and \( \theta \) are the estimated parameters. Equation (1) represents dynamic changes in the first moment (mean) of returns, while equation (3) describes time variations in the conditional second moment (variance). The return volatility is measured by the conditional variance from equation (3).

### 2.2 causality

The intraday causal dynamics of trading volume and return volatility can be examined in a vector autoregression (VAR) model:

\[ \sigma_t^2 = \gamma_1 + \sum_{k=1}^l a_i \sigma_{t-k}^2 + \sum_{i=1}^k b_i v_{t-i} + \sigma_{t-i} \]  

(4)

\[ v_t = \gamma_2 + \sum_{k=1}^l c_i v_{t-k} + \sum_{i=1}^k d_i \sigma_{t-i}^2 + \sigma_{t-i} \]  

(5)

where \( \sigma_t^2 \) is the conditional volatility of intraday stock returns, \( v_t \) is the natural log of trading volume during time interval \( t \), \( \epsilon_{it} \) is the disturbance reflecting variation of the left-hand-side variable that cannot be accounted for by the right-hand-side variables, and \( a, b, c, \) and \( d \) are the group lagged coefficients in the Granger-causality testing equations.
We test the intraday volume-volatility relation in the news and no-news samples. The SIAH is supported if we find significant causal link between volume and volatility in either direction in the presence of public news. In the absence of public news, however, SIAH predicts no significant causal link. Thus, we formulate the following hypotheses:

\[ H1: \text{During the times without public news, } \sum_{k=1}^{k} b_k = 0 \text{ in equation (4).} \]

\[ H2: \text{During the times without public news, } \sum_{k=1}^{k} d_k = 0 \text{ in equation (5).} \]

Two arguments under rationality may lead to rejecting H1 and H2. In efficient markets, the conditional mean price of a given stock is approximately equal to the true fundamental value plus a random error. Conditional volatility measures the degree of time-varying deviations of actual prices from their conditional mean. Under perfectly rational expectation, there should be no deviation of actual returns from their expected values in equilibrium. If a mispricing exists for some stocks, arbitrage would ensue to exploit any possible abnormal profits, causing higher volume. As rational traders take larger positions in the market, stock prices converge back to their fundamental values, and volatility should then fall. Therefore, under market rationality, an increase in trading volume causes a subsequent decrease in market volatility. Hence, we expect the causality from volume to volatility to be negative, \( \sum_{k=1}^{k} b_k < 0 \). As stock price reverts back to the expected intrinsic value, volatility declines and investors lose incentives to trade. Thus, we expect causality from volatility to volume to be positive, \( \sum_{k=1}^{k} d_k > 0 \).

2.3 data

In order to analyze various market conditions, we employ tick data of NYSE stocks from the NYSE Trade And Quote (TAQ) dataset for the one-month period of July 2002.
There are two reasons we chose July 2002 for our analysis. First, owing to the intensive efforts in hand-collecting intraday news from the media for over 200 NYSE firms needed for our analysis, we had to limit our sample to a one-month period. Second, we wanted to select a month where macroeconomic conditions in the U.S. were somewhat normal void of major economic and social crises that might negatively affect the overall market performance. July 2002 meets these criteria well.

We select firms with various market sizes, and exclude all exchange-traded funds (ETFs) listed in NYSE since ETFs are mutual funds and not regular companies. We divide our sample by large and small stocks to explore the size effect. Stocks with US$10 billion or more of market capitalization are selected for the large stock sub-sample. We picked the largest 300 stocks to ensure separation between small and large stock sub-samples.

To avoid the problem of infrequent trading, we exclude stocks with less than 8,000 observations for the month\(^1\). Doing so, we find that in general firms with market value of less than US$1 billion do not have high enough trading frequency. Thus we drop all firms smaller than US$1 billion in market capitalization. Consequently, our small stock sample consists of randomly selected firms with a market value between US$1-4 billion. The final sample contains 102 small stocks and 103 large stocks. We use the last transaction for each one-minute interval to construct the required one-minute price and return data. For the volume data, we aggregate the numbers of shares transacted within one-minute time blocks.

\(^1\) The requirement of 8,000 observations is based on the logic that there are about 430 trading minutes per day and 20 trading days per month. Thus, for the 1-month period, there are 8,600 observations if there is exactly 1 transaction per minute. Balancing the minimum required trading frequency and the number of firms available; we use 8,000 observations as our cutoff.
2.4 sampling procedure

To partition our return data into periods with and without public news, we employ FACTIVA, the global business news database provided by Dow Jones and Reuters, and identify all major public news published in the media from July 1 to July 31, 2002 for each of the 205 listing firms in our sample. We hand-collect the dates of the news publication for all companies. If a piece of news about a particular company appears in multiple media sources more than one time, we use the earliest date for that news and exclude the others. While most small stocks have less than 10 days with public news publications during the month of July 2002, almost all large stocks have news publications for at least 20 days in the same month. The no-news period for the small stocks is defined as the times on the trading days without any public news, whereas the news period comprises the trading days with public news.

Frequently, a variety of different news occurred on the same day for large stocks. Thus, we divide each trading day into six time slots (9.30 - 10.35, 10.36 - 11.40, 11.41 - 12.45, 12.46 - 13.50, 13.51 - 14.55, and 14.56 - 16.00 Eastern Standard Time) and record the news publication times into different time slots of the day. Sometimes news is announced when the market is closed (i.e., before 9.30 AM and after 4.00 PM EST). The first time slot of the day includes news publication from 12.00 at mid-night until the opening of the market next day, and the last time slot includes news publication from the close of the market until 12.00 mid-night of the day. The no-news (news) period for the large stocks consists of the trading time slots without (with) public news. We finally reach a total of 1812 news time slots for large stocks and 388 news time slots for small stocks.

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2 Major news items are defined as those that could potentially influence analyst forecasts and stock price movements such as announcements of technological breakthrough, mergers and acquisitions, earnings and dividends announcements, significant personnel changes, etc. Although somewhat subjective, we tried to choose only what appear to be "major news items". When we include more news items in our sample (which widens our news period), results are qualitatively the same.
3. Empirical Results

3.1 trading volume

We begin by examining trading volume. We split the volume data into two periods with and without public news releases. During the periods without public news releases, private information signals may still occur. Figures 1 and 2 plot the mean values of the log volume for all large and small stocks, respectively, for both the periods with and without public news releases. The grand means of the news and no-news periods are also presented. For large stocks (Figure 1), it is clear that the log volume average for the no-news period is clearly larger than that for the news period. Specifically, the grand mean of the log volume of the news period is 1.74, compared to a grand mean of 6.99 for the log volume of the no-news period. The difference between the two averages is highly significant (t-statistics=20.66). A similar message emerges for small stocks where the log volume for the news period is 1.30, while that for the no-news period is 5.64 (the t-value for the difference= 27.22). Thus, more trading activities take place during the no-news periods in which investors act solely upon private information signals. Blume, Easley and O'Hara (1994) contend that trading is induced by different beliefs of investors. Thus, the higher level of difference in beliefs across investors during these periods leads to more stocks being traded. As we saw, this outcome is insensitive to the size of stocks as it occurs with large and small stocks.

Insert Figures 1 and 2 about Here

3.2 return volatility

We now turn to examining return volatility. We plot the unconditional variances of one-minute returns of large and small stocks during the periods with and without public news. For most large stocks (Figure 3), the unconditional variance during the public news
period is higher than that during the no-news period. The grand mean of the variances is much higher in the public news period with a highly significant difference (t-value = 3.90). In the case of small stocks (Figure 4), although the average variances also appear higher in the public news period, the difference between the average variances during the two periods is not statistically significant (t-value = 1.10). Therefore, the volatility of large stock returns reacts to public news more strongly than does volatility of small stock returns.

Another metric to investigate volatility behaviour is the concept of excess volatility proposed by DHS. Excess price volatility is the difference between the level of unconditional volatility and the level of volatility when the noise variance is perceived correctly. Let $\sigma^2_{R,t}$ be the volatility if all individuals were rational. Then the volatility levels can be derived from an expectation model such as the EGARCH-M model described above. We define the proportion of excess volatility relative to the average (rational) market as follows:

$$VR = \frac{\sigma^2 - \overline{\sigma^2_{R,t}}}{\overline{\sigma^2_{R,t}}}$$  \hspace{1cm} (6)

where $\sigma^2$ is the unconditional variance and $\overline{\sigma^2_{R,t}}$ is the average conditional volatility based on an EGARCH-M model.

We estimate the EGARCH-M system of equations (1)-(3) jointly using predicted values of $\sigma^2_t$ obtained from equation (3) to represent the conditional variance. We use an EGARCH-M (1,1) model for each of the 205 stock returns (102 small stocks and 103 large stocks) and extract the associated conditional variance to represent their return volatilities. We then compute the variance ratio using equation (6). Figures 5 and 6 plot the variance ratios for larges and small stocks, respectively. In the case of large stocks, the variance ratios for the periods with public news are generally larger than those for the periods without public news. The average variance ratio for the news periods is 1.54, which is much higher than that for
the no-news periods (0.97). For small stocks, the picture is not as clear, though the average variance ratio of the news periods (1.08) is still slightly higher than that of the no-news periods (0.95). Thus, results from the DHS variance ratios confirm our earlier findings from volatility plots as they both imply that return volatility reacts more strongly to public news, especially for large stocks. This evidence is also consistent with the results of Theobald and Yallup (2004) that, compared to small stocks, large stocks have higher speeds of adjustments to price deviations from intrinsic values and hence exhibit a more volatile price movement.

Insert Figures 5 and 6 about Here

3.3 causal link under no-news

Next, we examine the dynamic relations between trading volume and return volatilities. Having measured intraday volatility, we proceed to testing our proposed hypotheses H1 and H2. We estimate regressions (4) and (5) with up to 20 lags and introduce necessary adjustments to the standard errors for heteroskedasticity and serial correlation of residuals for up to 20 lags. To investigate hypotheses H1 and H2, we calculate the corresponding F-statistics and test the joint significance of the lagged coefficients in each equation to derive Granger-causality inferences.

Standard tests of significance can be misleading if the sample size is extremely large (Zellner, 1984). The problem arises since very large samples, like ours, reduce the standard errors of the estimates, leading to the rejection of almost any null hypothesis. One appropriate approach for resolving this large-sample problem is to use Zellner’s (1984) Bayesian approach that adjusts the critical values of the F-tests according to the sample sizes (further details are delegated to the Appendix).

To facilitate exposition, we use graphical presentation to discuss our results from the Granger-causality tests. Figures 7 to 14 plot the summed lagged coefficients of the Granger-
causality tests and the associated F-statistics, along with the Bayesian adjusted critical values for each stock. Figure 7 shows that, for large stocks over the period without public news, each summed lagged coefficient of trading volume in equation (4) is positive (i.e., $\sum_{k=1}^{L} b_k > 0$), and the vast majority of the associated F-statistics are above the Bayesian adjusted critical values (represented by the flat line at the bottom of the figure). These positive sums of causal coefficients $\sum_{k=1}^{L} b_k$ are inconsistent with the rationality presumption that trading smooth price fluctuations by closing the gap between actual price and the intrinsic value. On the other hand, this finding may suggest that, without public news, investors overestimate the precision of their private signals and trade excessively leading to higher subsequent volatility. In any case, our finding of a significant causal relation in the absence of public news is inconsistent with the SIAH since it predicts a causal relation only in the presence of public news. Figure 8 depicts the results from testing the reverse causality for large stocks during no-news periods. As can be seen, none of the F-statistics is significant according to the Bayesian adjusted critical values. This does not accord well with the rationality view that when volatility declines and price reaches equilibrium, investors lose incentives to trade. Hence, our results do not support the rationality argument for a bi-directional causality between volume and volatility. Rather, the results imply that investors trade too aggressively based on private signals, but they are unwilling to close their positions afterwards. A similar message emerges for small stocks (Figures 9 and 10).

3.4 re-examining the sequential information arrival hypothesis

As discussed above, the SIAH is better tested with a sample that contains public news signals to ensure the existence of genuine information arrival. Figures 11-14 display our results from testing Granger-causality between volume and volatility during the time periods...
with public news. As these figures reveal, there is strong evidence for causal relations between volume and volatility in both directions for large as well as small stocks. Such a finding is consistent with Darrat, Rahman and Zhong’s (2003) support for SIAH.

4. Further Discussion and Implications

Three main findings emerge from our empirical analysis. First, investors trade more heavily in the no-news period than they do in the news period. Second, return volatility is more pronounced in the public news period than in the no-news period. And third, there is a bi-directional causality between volume and volatility in the public news period. In the absence of public news, causality runs one way from volume to volatility is significant. While it is possible that our results may be rooted in some anomalies, it seems more likely that these findings are consistent with the overconfidence and biased self-attribution model of DHS.

Indeed, overconfidence, even in the absence of new information, could explain the observed intraday relation between trading volume and return volatility. Overconfidence behavior can incite higher trading volumes. When overconfident investors take larger positions than justified by rational behavior, prices tend to drift further away from their true fundamental values, leading to higher volatility. Thus, as in the SIAH, investors’ overconfidence suggests the presence of a positive causal link from trading volume to return volatility.

According to DHS, an overconfident investor is one who overestimates the precision of only his own private information signal, but not the precision of information signals publicly received by all investors. By overreacting to private signals, overconfident investors create excessive price movements. With the arrival of public information, any price deviations begin to correct themselves. As public information continues to flow in the
market, prices move closer to their full-intrinsic values. Thus, stock prices overreact to private information signals but underreact to public news signals.

Before relating our results to the DHS model, we first outline the model’s main points. DHS assume that traders receive private information signals before they receive public information. Figure 15 modifies a similar figure in DHS (1998) which shows how stock prices react to private and public information signals. Times 1-3 are the time intervals that are sufficiently long to capture the process of news arrival. Assume further that investors process the information and adjust stock prices accordingly in a constant speed within each time unit. If we begin with no signal, the price is equal to the rational expected value, $P_0$. Let a private signal arrive at the beginning of time 1. Since overconfident investors react excessively to this private signal, the stock price overreacts. The solid curve represents the average time path of stock prices following a positive (upper curve) or negative (lower curve) private and public signals. The dotted curves represent the fully rational price movements following these signals. The dot-dash curve reflects price movements when there is a biased self-attribute effect (which will be discussed in more details below). At the beginning of time 2, public information signal arrives. As a result, the inefficient price deviation is partially corrected as depicted by the downward movement of the solid curve. This correction phase extends to the subsequent public information arrival until the information is fully revealed and consumed.

This multi-phase model sheds light on intraday trading volume. Overconfidence behavior implies that differing beliefs more likely occur during the times when private (as opposed to public) information signals arrive. When the private signal arrives at time 1 (when there is no public news), overconfident investors and rational investors form different beliefs.

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3 As in DHS, it is assumed that at least some noisy public information arrives after a private signal. However, the model implications still stand even without this simplifying assumption.
about the full-information value of the stock [Blume, Easley and O’Hara (1994)]. This difference in beliefs causes trading volume to increase. However, when public information is fully revealed at time 2 (during the times with public news), there would be smaller difference in beliefs between overconfident investors and rational investors, causing trading volume to fall. Thus, trading volume is higher during the times without public news than during the times with public news. This implication is consistent with our results (see Figures 1-2).

To a lesser extent, trading may be induced by rational motives that are not captured by firm-specific public news identified in our sample. Liquidity needs such as 401(K) investments, end of month sales, market wide news on interest rate and employment figures, or news relating to competitors may all create more trading. However, these rationally induced trades are insufficient by themselves to explain why there is systematically higher trading volume during the no-news period than during the news period. Specifically, liquidity induced trading is relatively trivial and should not constitute the major volume of trades in intraday trading. Our one-month sample period of July 2002 is relatively ‘quiet’ and does not contain prominent market wide news that could have triggered investors’ portfolio rebalancing. Any unidentified public news such as news relating to competitors will change the stock’s fundamental value by altering the expectations of future cash flows and/or required returns. As discussed above, rational trading based on such news should reduce the discrepancy between the current price and the fundamental value and hence reduce the return volatility. However, our results show that trading volume does not reduce subsequent volatility but rather increase it. Therefore, our finding of systematically higher trading volume across almost all stocks (large and small) in our random sample implies that excessive trading in the absence of public news may very well be attributed to overconfidence sentiment.
We turn next to possible implications for intraday volatility. DHS argue that overconfidence is not static but rather dynamic and time-varying. If an investor trades based on a private news signal, his confidence will rise when a public news signal released later confirms his trading action (i.e., the good news arrives after his buy or bad news after his sell). On the other hand, the subsequent arrival of contradictory public information causes the investor’s confidence to fall only modestly, if at all. This is the hypothesis known as biased self-attribution of DHS. Therefore, public information can trigger further overreaction to a preceding private signal. As depicted by the dot-dash curve in Figure 15, biased self-attribution causes the price to further deviate from the rational price and hence drives volatility up at time 2. Hence, we can test the biased self-attribution hypothesis of DHS by testing its implication that return volatility during the times with public news is higher than that during the times without public news. Our results support such a contention (see Figures 3-4). With the arrival of public information that confirm preceding private signals, overconfident investors would temporarily overreact, pushing the price further away from the full-information rational price, leading to higher volatility. Small stocks often have weak biased self-attribution effect partly because investment professionals (e.g., fund managers and institutional investors) who tend to be overconfident and biased toward self-attribution usually trade larger stocks.\footnote{For example, Falkenstein (1996) and Nielsen (2004) find that mutual funds prefer liquid and large stocks.}

Our finding of a positive, uni-directional causality from volume to volatility also supports the DHS model. Overconfident investors over-estimate the precision of their private signals in the no-news period, leading to differing opinions about the stock value. Thus, investors trade excessively driving the stock price away from its intrinsic value. This process increases volatility, even though there is no observable public signal to justify the increased
volatility. Note that a positive causality from volume to volatility is contrary to the prediction from rational trading since increased trading of rational investors should bring the price back to its intrinsic value, thus reducing volatility.

One might argue that overconfident investors who engaged in excessive trading will need to unwind their positions after opening up positions that incited volatility. However, it is unclear whether or not such overconfident traders will be willing to close their positions. When a genuine public information signal is revealed, quasi-rational traders do not necessarily trade immediately. Prior research [e.g., Ferris, Haugen and Makhija (1988) and Odean (1998)] suggests that investors are reluctant to keep holding losing stocks (i.e., the disposition effect). With excessive trading, overconfident traders would unlikely realize any gain from the trade and may be unwilling to close their positions at the appropriate times. Thus, overconfidence behavior is inconsistent with a reverse causality from volatility to volume. That is, past volatility information cannot explain current trading volume. Our results (Figures 8 and 10) that volatility does not Granger-cause volume in the no-news period are consistent with the notion of disposition effect.

5. Conclusion

Prior research on intraday dynamic relations between return volatility and trading volume cannot distinguish between the sequential information arrival hypothesis (SIAH) and other possible behavioral interpretations. In particular, the SIAH is based on rational behavior and implies certain lead-lag relations between volume and volatility only with the arrival of new public information. In this paper, we separate our intraday data into periods with and without public news. Unrelated to the SIAH, we find that volume unidirectionally Granger-causes volatility even during the periods without public news. These results suggest that investors trade too aggressively based on private news, triggering excessive return volatility in the no-news period.
Our results are consistent with the overconfidence and biased self-attribution model of DHS, which suggests that investors are overconfident and may trade excessively according to their private signals. When public signals confirm their private information signals, investors tend to overreact to the arrival of the public signals, producing a higher level of return volatility in the news-period compared to the no-news period. Moreover, our results suggest that investors are reluctant to close their positions afterwards, a symptom of disposition effect.

In the period with public news, we find significant bi-directional causality between volume and volatility in accordance with the SIAH. These findings suggest that future research into the SIAH should use sampling procedures similar to those proposed in this paper in order to avoid contaminating the results with behavioral effects.
References


Appendix: Zellner’s posterior-odds-ratio approach for adjusting critical values

This appendix presents a technical summary of how we adjust critical values for large sample size in all of our statistical tests using the Bayesian theorem. Bayesian theorem is based on the definition of conditional probability. The probability that a hypothesis (H) is true after observing the data (usually called the posterior probability), \( P(H|D) \), is defined as

\[
P(H | D) = \frac{P(D | H)P(H)}{P(D)} \quad (A.1)
\]

where \( P(D|H) \) is the probability of observing the data given that H is true (called the likelihood); \( P(H) \) is the probability that H is true before observing the data (called the prior probability); \( P(D) \) is the unconditional probability of observing the data regardless of H.

Take the Granger-causality test in the context of volatility equation (4) for example. We want to examine the null hypothesis \( (H_{A1}) \) that volume does not Granger-cause volatility, i.e.,

\[ H_{A1}: \text{all } b_k = 0, \ (k=1,2, \ldots, L). \]

Hence, the alternative hypothesis \( (H_{A2}) \) is that volume Granger-causes volatility, i.e.,

\[ H_{A2}: \text{not all } b_k = 0, \ (k=1,2, \ldots, L). \]

Therefore, the posterior probabilities of the two hypotheses are, respectively,

\[
P(H_1 | D) = \frac{P(D | H_1)P(H_1)}{P(D)}, \quad (A.2)
\]

\[
P(H_2 | D) = \frac{P(D | H_2)P(H_2)}{P(D)}. \quad (A.3)
\]

Thus, the ratio of the two posterior probabilities (called the posterior odds ratio) is

\[
K_{12} = \frac{P(H_1 | D)}{P(H_2 | D)} = \left( \frac{P(D | H_1)}{P(D | H_2)} \right) \left( \frac{P(H_1)}{P(H_2)} \right), \quad (A.4)
\]
The first term on the right-hand side is called the likelihood ratio. The second term on the right-hand side is called the prior odds ratio, and assumed to be one if both hypotheses are equally probable. $H_{A1}$ and $H_{A2}$ involve some parameters, say $\beta_1$ and $\beta_2$. The likelihood ratio is computed by a weighting procedure, where the weights are determined by the prior distributions of these parameter sets. Thus, the posterior odds ratio can be rewritten as:

$$K_{12} = \frac{\int L_1 P_1(\beta_1) d\beta_1}{\int L_2 P_2(\beta_2) d\beta_2} \frac{P(H_1)}{P(H_2)},$$

(A.5)

where $L_1$ and $L_2$ are the respective likelihoods, and $P_1$ and $P_2$ are the respective prior distributions for the parameters implied by hypotheses $A1$ and $A2$. The first term on the right-hand side is sometimes called the Bayes factor.

Zellner and Siow (1980) show that, with prior odds ratio equal to one, the posterior odds ratio can be approximated by

$$K_{12} = \frac{\pi^{1/2}}{\Gamma((k + 1)/2)} \left[ 1 + \frac{k F_{k,T-k-1}}{k + 1} \right]^{(T-k-2)/2},$$

(A.6)

where $T$ is the sample size, $k$ is the number of restrictions implied by the null hypothesis relative to the alternative hypothesis, $A = \frac{\pi^{1/2}}{\Gamma((k + 1)/2)}$, $\Gamma(\bullet)$ is the gamma function, and $F_{k,n-k-1}$ is the standard $F$ statistic for testing the null hypothesis versus the alternative. The hypothesis choice is undertaken with explicit consideration of losses (mistakes) associated with the incorrect choice. Assuming that the parameters to be tested are uniformly distributed over their respective range, the expectation of the total fraction of mistakes associated with both hypotheses will be minimized by using the critical value $K_{12}=1$ [see Zellner (1984), p.289]. That is, if $K_{12}>1$, choose $H_{A1}$, and if $K_{12}<1$, choose $H_{A2}$. 
As can be seen in equation (A.6), the posterior odds ratio $K_{12}$ is a monotonic function of the standard $F$ statistic. This fact makes it easy to obtain the sample-size-adjusted critical values of $F$ statistics. Any test procedure that rejects $H_{A_1}$ if $K_{12} < 1$ is equivalent to the procedure that rejects $H_{A_1}$ if $F_{k,n-k-1} > F_c$, where $F_c$ is a critical value corresponding to the unity posterior odds ratio. Hence, the Lindley’s Paradox can be resolved by adopting the new critical value $F_c$ in the $F$ test. Specifically, the critical value of $F_c$ for $K_{12}$ to be 1.0 is

$$F_c = \left\{ \exp\left[ \frac{2}{T - k - 2} \ln\left( \frac{\mathcal{A}(T - k - 1)/2^{1/2}}{K_{12}} \right) \right] - 1 \right\} \left( \frac{T - k - 1}{k} \right). \quad (A.7)$$
Figure 1

Difference in Average Volume between News and No News Periods

Avg of mu1 minus avg of mu2 = 5.241  cross-sectional t-stat = 20.66
Figure 2

**Difference in Average Volume between News and No News Periods**

- **Log Volume**
- **Small Stocks**

- Mean of the news period (\(\mu_1\))
- Mean of the nonews period (\(\mu_2\))
- Avg of \(\mu_1\) = 1.296
- Avg of \(\mu_2\) = 5.636

**Average of \(\mu_1\) minus Average of \(\mu_2\) = 4.339**

**Cross-sectional t-stat = 27.22**
Difference in Average Volatility (Unconditional Variance) between News and No News Periods

Figure 3

avg of mu1 minus avg of mu2 = 2.86E-06   cross-sectional t-stat = 3.90
Difference in Average Volatility (Unconditional Variance) between News and No News Periods

Figure 4

Difference in Average Volatility (Unconditional Variance) between News and No News Periods

Mean Volatility

Small Stocks

mean of news period (mu1)
mean of nonews period (mu2)
avg of mu1
avg of mu2

avg of mu1 minus avg of mu2 =2.22+E-06  cross-sectional t-stat = 1.10
Unconditional Volatility to Conditional Volatility Ratio
of Noews & News Period

Figure 5

Large Stocks

mean of news period (mu1)  mean of nonews period (mu2)  mu1-mu2

Avg of mu1 = 1.54  Avg of mu2 = 0.97
Figure 6

Unconditional Volatility to Conditional Volatility Ratio of Nonews & News Period

Small Stocks

- mean of news period (mu1)
- mean of nonews period (mu2)
- mu1-mu2

Avg of mu1 = 1.08  Avg of mu2 = 0.95
Figure 7

Volume Granger-cause Volatility (No News Period)

![Graph showing the sum of causal coefficients and F-test statistics for large stocks with Bayesian adjusted critical value.](image-url)
Figure 8

Volatility Granger-cause Volume (No News Period)

Sum of Causal Coefficients

F-Test Statistics

Large Stocks

Bayesian Adjusted Critical Value
Figure 9

Volume Granger-Cause Volatility (No News Period)

Sum of Causal Coefficients

F-Test Statistics

Small Stocks

Adjusted Bayesian Critical Value
Figure 10

Volatility Granger-Cause Volume (No News Period)

Sum of Causal Coefficients

F-Test Statistics

Small Stocks

Adjusted Bayesian Critical Value
Figure 12

Volatility Granger-cause Volume (News Period)

-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
1.2

sum of Causal Coefficients

Large Stocks

F-Test Statistics

Bayesian Adjusted Critical Value
**Figure 13**

Volume Granger-cause Volatility (News Period)

![Graph showing Volume Granger-cause Volatility (News Period)](image)

F - Test Statistics

Bayesian Adjusted Critical Value

Small Stocks
Volatility Granger-Cause Volume (News Period)

Figure 14

Volatility Granger-Cause Volume (News Period)

Sum of Causal coefficients

Small Stocks

F - Test Statistics

Bayesian Adjusted Critical Value
Figure 15
Expected Price Movement of a Private Information Signal followed by a Public Information Signal

Figure 15 shows the expected price movement of a private information signal followed by a public information signal. The graph illustrates the price movement over time, with different lines indicating different scenarios:

- **With Attribution Bias**
- **Without Attribution Bias**

The x-axis represents time, while the y-axis represents the expected price. The graph includes the following key events:

- **Arrival of Favorable Private Signal**
- **Arrival of Favorable Public Signal**
- **Arrival of Unfavorable Private Signal**
- **Arrival of Unfavorable Public Signal**

The figure highlights how the introduction of public information can lead to different price movements compared to scenarios with and without attribution bias.