Underreaction, Trading Volume, and Post-Earnings Announcement Drift*

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ABSTRACT

In this paper, we develop a simple model in which trading volume contains information about future stock returns. Specifically, our model explains why high trading volume is observed when a firm announces earnings news and how trading volume can be related to the initial underreaction of the stock price. Our model has a clear testable implication that high abnormal trading volume predicts a stronger drift. We test our model's implication and find strong evidence for the model in the case of positive news. Weaker evidence is found in the case of negative news. We also discuss possible explanations for the asymmetric informativeness of trading volume.

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1. Introduction

Ball and Brown (1968) are the first to find that the abnormal return of firms with positive earnings news continues to drift upward after the earnings announcements and that the opposite is true for firms with negative news. Since then, many researchers have extensively investigated the post-earnings announcement drift. Bernard (1993) writes an excellent survey paper dealing with the underreaction of stock prices to announcements of companies' earnings. He conjectures that market participants do not recognize the positive autocorrelations in earnings changes but in fact believe that earnings follow a random walk. In this case, investors do not fully reflect the news content of earnings announcements and a subsequent drift can be observed. Recently, there have been several attempts to explain investors' underreaction.[1] Barberis, Shleifer and Vishny (1998, henceforth BSV) provide a formal model to explain underreaction to earnings announcements.[2] Their explanation of underreaction to earnings announcements is related to investors' conservatism. Conservatism refers to the reluctance of individuals to update their beliefs upon receiving new information (Edwards, 1968). Conservatism fits the underreaction story very well. Investors subject to conservatism might disregard the full information content of an earnings (or some other public) announcement because they tend to cling, at least partially, to their prior estimates of earnings rather than update their estimates based on the new information contained in the earnings announcement. Daniel, Hirshleifer, and Subrahmanyam (1998, henceforth DHS) show that when investors overestimate the precision of private signals, they can generate an initial price reaction that is weaker than the fully rational one. In their model, investors do not react much to public signals when the content of the new information conflicts with their private signals.[3] Hong and Stein (1999, henceforth HS) provide a model in which private information diffuses slowly. In their model, "newswatchers" fail to form sophisticated forecasts of future stock prices since they make forecasts based only on private signals they observe and do not condition their estimates on past or current prices. In this case, stock prices will exhibit momentum. HS also explain how their model could generate underreaction to public information. Although the news announcement itself is public, it may require other private information (e.g., knowledge of the stochastic processes governing earnings) to convert the news into a judgment about value.

In this paper, we try to capture the degree of underreaction of stock prices and its effect on the magnitude of the drift after earnings announcements by looking at trading volume. We pay attention to the fact that abnormally high trading volume, unrelated to the magnitude of price changes, is generated around earnings announcements. Kandel and Pearson (1995) show that even when there is little price change, a considerable amount of abnormal trading volume exists around earnings announcements. They interpret this as evidence of the existence of heterogeneity among investors in interpreting the content of earnings announcement news. We fully agree with their assessment, but we go one step further and investigate the sources of differences in investor interpretations and their implications on drift patterns.

This paper assumes heterogeneity in the belief-updating processes among investors. The assumption of heterogeneity in investors' beliefs is not new, and in fact we have a variety of theoretical and empirical evidence that supports this hypothesis. Kim and Verrecchia (1993) develop a model in which the precision of pre-announcement public and private information affects trading volume. Kandel and Pearson (1995) suggest a model of differential interpretations of public information. Harris and Raviv (1993) also suggest a similar model in which investors disagree on the importance of public news. In the psychological literature, Griffin and Tversky (1992) suggest that the experts and the novices may react differently to new evidence.

In our model, we assume two types of investors. The first type of investors is fully rational in the sense that they follow Bayes' rule in updating their posterior beliefs. The second type of investors is those who put irrationally low weight on news. We show that the degree of underreaction can be captured by the weight these investors put on news and that the weight can be recovered from trading volume data.

In this case, trading volume can arise as a result of the interaction between these two groups of investors; moreover, it has informative implications for the subsequent drift pattern. As the weight that the second type of investors puts on news decreases (i.e., the more conservative investors become), we observe higher trading volume as a result of the interaction between the two types of investors, and the initial price reaction to earnings announcements should be less than the rational level (i.e., the level when there are no underreacting investors). Consequently, there should be a subsequent price adjustment (drift) following an earnings announcement when the initial price reaction does not fully reflect the information contained in the earnings announcement. Since rational-level price change is unobservable, only by looking at the trading volume could we infer whether price underreacts to news or not. This is the unique role of trading volume in our paper.

In our model, we focus on the "news characteristics" of earnings announcements as a determinant of the degree of underreaction. To understand this statement, consider two firms that share the same firm characteristics (e.g., market capitalization, institutional ownership, analyst coverage). Even though the two firms' announcements generate the same magnitude of surprise in terms of standardized unexpected earnings (SUE), the reaction of investors might differ depending on the characteristics of the news. If the value implication of the news is really clear, the weight that the second type of investors places on the news will converge to the rational level and there will not be much trading volume. However, if the content of the news is murky at best, the same level of earnings-surprise would generate much higher trading volume and price will not rise as much as in the previous case where the information content is clear.

In other words, we argue that the magnitude of conservatism could depend on the news characteristics and that might be well captured by abnormal trading volume. In our empirical work, we carefully proceed to measure abnormal trading volume that is not correlated with firm characteristics and depends only on the news characteristics. A similar argument can be found in Klibanoff, Lamont, and Wizman (1998). They test the behavioral hypothesis that investors underreact less to news that is salient. They test investors' reaction to salient news in closed-end country funds and measure saliency by the appearance on the front page of *The New York Times*. They find that the price of a closed-end country fund reacts more strongly to news about its fundamentals when the country whose stocks the fund holds appears on the front page of the newspaper.

Our paper also contributes to research on understanding what information trading volume contains in addition to the information that is contained in the return data. Blume, Easley and O'Hara (1994) show that information quality that can not be deduced from price statistics can be inferred from trading volume data. In this paper, we argue that trading volume can generate additional information about future stock returns since it captures the degree of clarity of information[4] contained in earnings announcements.

Our research stands out from the others in the literature that investigates volume and return relationships in that we focus specifically on an informational event. Some papers look at trading volume and return relationships when there is no information asymmetry (e.g., Campbell, Grossman, and Wang (1993) and Conrad, Hameed, and Niden (1992)), while others look at trading volume and return autocorrelation patterns in relation to information asymmetry due to the existence of private information (Llorente, Michaely, Saar and Wang (2000)). Recently Swaminathan and Lee (1999, 2000) investigate trading volume and earnings announcements but in a different context. They look at the implications of past trading volume for price momentum.[5] Gervais, Kaniel, and Mingelgrin (2001) find that stocks experiencing unusually high trading volume over a day or a weekend tend to appreciate over the course of the following month. They argue that trading volume could be a good proxy for the level of investors' interest in the stock and thus the visibility of the stock captured by trading volume could explain future stock returns quite well. Pritamani and Singal (2001) investigate return dynamics when firms experience extremely large price changes around several corporate events. They find that subsequent returns move in the same direction as the initial price changes when large price change is accompanied by large trading volume. Our study differs from theirs in that we do not confine our sample to firms that experience extremely large price changes.

We look at all NYSE and AMEX firms that made earnings announcements during the 1988-1996 period to test our model's prediction.[6] We develop a measure of volume that is not correlated with the magnitude of the initial price reaction to the news and firm characteristics. This measure of volume is defined as the residual from the cross-sectional regression of volume on price changes and firm characteristics. We find that in the cases of positive news, our model's prediction is strongly supported in every specification we use to calculate the residual volume. High (low) residual volume that is generated due to an earnings announcement implies a stronger (weaker) drift. However, we could find only weak evidence for the relationship between abnormal trading volume and the subsequent drift for the cases of negative news (the results vary somewhat depending on, for example, which surprise measure we use). This asymmetry in itself is interesting to note. We conjecture that the weak evidence for the informativeness of trading volume for future drifts may be due to institutional arrangements that our model cannot capture, e.g., short-sales constraints. For instance, some institutional investors, such as mutual funds, do not usually take short positions. In this case, the low residual volume we calculate may not be due to news characteristics but due to the restriction that some investors must sit back from the trading scene because of the short-sales constraint. Thus for negative news, the residual volume we calculate is subject to additional noise relative to the one we calculate for positive news and it may not serve its purpose well as a predictor of drift. Diamond and Verrecchia (1987) and Chen, Hong, and Stein (2000) look at the implications of short-sales constraints for stock returns in relation to private information.

The paper is structured as follows. Section 2 presents a model that shows how trading volume could be a good proxy (after necessary adjustments) for news characteristics that are crucial to investors' underreaction. Section 3 and 4 contain our main empirical results on the relationship between trading volume and drift. Section 5 concludes.

2. Conceptual framework

2.1. Model

We make the following assumptions[7].

(1) There are two kinds of assets: a riskless asset with a zero rate of return, and a risky asset with an uncertain payoff R. The supply of the risky asset is normalized at 0.

(2) There are three time periods. At time 1, investors have access to pre-disclosure information about the firm, and form symmetric prior beliefs about R. At time 1, the symmetric prior belief of investors is represented by a normal density with mean X and precision Z.

(3) At time 2, a public signal is announced, and investors update their beliefs. The public signal at time 2 is given by $L = R + \varepsilon$, where ε is normally distributed with mean zero and precision b. Here the precision parameter b can be interpreted as the informativeness of the public signal about the stock's future value. At time 3, R is realized, and investors consume their wealth.

(4) There are two types of investors indexed by i=1, 2, depending on how they react to earnings news. The first type of investors, whose proportion is α, is the underreacting investors. Their *perceived* precision of the public signal is lower than the *true* precision, but the extent to which the perceived precision diverges from the true precision depends on the saliency of the public news. The assumption that the perceived precision is lower than the true precision reflects the psychological evidence that individuals update their posterior beliefs too little relative to the rational Bayesian benchmark. This type of investors underestimates the degree to which the public news is correlated with the future

firm value, and puts too much weight on their prior beliefs. We assume that the perceived precision of the public signal to the first type of investors is $\omega \cdot b$, where $\omega \leq 1$ and ω increases with the saliency of the news. Thus if the content of the news is clear (or salient) enough, ω is close to 1 and even the first type of investors will behave as if they were fully rational Bayesian investors who perceive the precision of the public information correctly as b.

(5) The second type of investors, whose proportion is $1-\alpha$, is rational in the sense that their perceived precision equals the true precision of the public signal. They have the ability to correctly interpret the importance of the public news for the stock's future value. This type of investors can be thought of as risk-averse arbitrageurs who are free from the psychological biases mentioned above. After the public signal is revealed, they update their beliefs in a correct way according to Bayes' rule.

(6) All investors maximize the expected utility of third-period wealth. The utility function takes on the exponential form, $U(W) = -e^{-W}$.

A. Time 1

All investors choose their demands (*m*) of the risky asset to maximize their expected utility of the third-period wealth.

$$\max_{m} E_1(-\exp[-m \cdot (R - P_1)]) \tag{1}$$

where $E_1(\cdot)$ represents expectation with respect to the prior belief of investors. P_1 is the first-period price. The resulting demand for the risky asset can be represented as follows:

$$m = (X - P_1) \cdot Z \tag{2}$$

Using the market equilibrium condition, we can calculate the first-period equilibrium price.

$$P_1 = X \tag{3}$$

The first-period equilibrium price is equal to the mean of the prior belief distribution of investors.

B. Time 2

After the public signal is revealed, investors update their beliefs, and the second round of trading occurs. The posterior belief of the rational investors is given by a normal density with mean Y_2, where Y_2 can be expressed as follows:

$$Y_2 = E_{22}(R|L) = \rho_2 \cdot X + (1-\rho_2) \cdot L \tag{4}$$

Here $\rho_2 = Z/(Z+b)$ denotes the relative weight put on the prior belief by the rational investors. Precision of the posterior belief is $Z+b$. $E_{22}(\cdot)$ represents the expectation with respect to the information set of the second type of investors at time 2.

The mean Y_1 of the posterior belief of the underreacting investors is given by the following:

$$Y_1 = E_{12}(R|L) = \rho_1 \cdot X + (1-\rho_1) \cdot L$$
$$\text{where } \rho_1 = \frac{Z}{Z+\omega \cdot b} \tag{5}$$

In equation (5), ω is the parameter of importance. This is the parameter that will determine the degree of underreaction in the model. It is important to note that ω represents news characteristics. As the saliency of the news becomes lower, ω decreases and the underreacting investors put less weight on public signals in updating their beliefs.

We can see that the weight the underreacting investors put on their prior belief, $\rho_1 = \dfrac{Z}{Z + \omega \cdot b}$, is greater than that of the rational investors. In brief, the underreacting investors are overconfident about their prior beliefs.

The equilibrium price will be determined by the interaction of these two types of investors and can be calculated as follows:

$$P_2 = \frac{Z \cdot X + L \cdot \hat{b}}{Z + \hat{b}}, \text{ where } \hat{b} = [\alpha \cdot \omega + (1\text{-}\alpha)] \cdot b \tag{6}$$

When we compare P_1 and P_2, it can be shown that the price change between the two periods is linearly related to the surprise component of the public signal.

$$\begin{aligned} \Delta P = P_2 - P_1 &= \frac{\hat{b}}{Z + \hat{b}} \cdot Surprise \\ Surprise &= L - E_1(L) = L - X \end{aligned} \tag{7}$$

If the content of the news is so clear as to make even the first type of investors behave as if they were rational investors, the price change would be

$$\Delta P = P_2 - P_1 = \frac{b}{Z + b} \cdot Surprise \tag{8}$$

Since $\dfrac{b}{Z+b} \geq \dfrac{\hat{b}}{Z+\hat{b}}$, the price change in response to public news is less than the fully rational level.

Equation (7) shows that as the saliency of the public news becomes lower (so ω becomes lower), the underreacting investors will underestimate the importance of the earnings news by more, the weighted average of the perceived precision of the public signal ($\hat{b}$) becomes lower than the true precision (b), and therefore the price change in reaction to the news will be less than the rational level. If the post-announcement drift emerges as an adjustment process due to an irrationally small initial price reaction to the news, the lower saliency of the news will lead to a greater magnitude of the drift afterwards.

However, there is no way to quantitatively measure the saliency of news by looking at the price change alone since we cannot infer the amount by which the initial price reaction differs from the fully rational level. But trading volume around an earnings announcement can help us make this inference.

Trading volume in reaction to the public signal would be the absolute value of the change in the holdings of one type of investors and can be expressed as follows:

$$Volume = |\Delta P| \cdot \alpha(1-\alpha) \cdot Z \cdot \frac{1}{(\frac{1}{1-\omega} - \alpha)} \tag{9}$$

In equation (9), we can see that as ω increases (i.e., the news is more salient), trading volume will be lower for a given magnitude of the price change. When the public news is more salient, the underreacting investors incorporate more of the information content of the news into their posterior beliefs, and therefore, the difference in the interpretation of the public news between the rational investors and the underreacting investors becomes smaller, hence leading to low trading volume. At the extreme, if $\omega = 1$, then all investors are updating their beliefs using the true precision and there will be no trading volume. As the saliency of the news becomes lower, the difference in the interpretation of the news between the two types of investors increases, and larger trading volume will be induced.

When positive news is announced ($L - E_1(L) > 0$), the price will fail to rise to the fully rational level, and the underreacting investors, who do not update their beliefs in the face of new evidence by as much as the rational investors, will have lower expectations of the future stock value than the rational investors. Therefore underreacting investors will try to sell stocks and rational investors will buy from them. On the other hand, when negative news is announced ($L - E_1(L) < 0$), the price will fail to go down to the fully rational level, and the underreacting investors, who did not adjust their posterior beliefs as much as the rational investors, will become buyers, and the rational investors will become sellers.

In equation (9), we can see that the trading volume is correlated with three components. First, volume is positively correlated with the magnitude of the price change as long as there exists some degree of differential interpretation about the news content.

Second, volume will also be influenced by the firm characteristics that are related to the precision of pre-disclosure information (Z) and the proportion of rational investors ($1-\alpha$) among the firm's clientele.

Last, trading volume is related to the degree of underreaction and the news characteristics that influence it. Public news that has clear value implications for a stock, such as the announcement of a takeover bid at a specific price, will induce lower trading volume. But when it is not easy to interpret the content of the public news, the reaction of the two types of investors differs and larger trading volume will be observed. Also, high saliency of the news will reduce the degree of underreaction by the first type of investors.

Equation (9) is a very important benchmark for the empirical part of the paper. Controlling for the price change and other firm characteristics that might be related to the level of α and Z[8], we can capture the part of the trading volume that is related to the news characteristics and has drift implications.

2.2. Identifying the degree of underreaction

In our model, the price change is less than the rational level, due to the existence of investors who do not give rational weight to the public news in updating their beliefs. However, we are not able to identify the degree of underreaction by observing the price change alone, because the true surprise component of the public news is unobservable and the saliency of the news is not quantifiable. But we can infer the degree of underreaction, ω, using the trading volume after controlling the price change and firm characteristics. Suppose there are two firms with identical firm characteristics (therefore the same α and Z). On the day of the earnings announcement, one firm exhibits a 2% price change with zero volume. The other firm also exhibits a 2% price change but with high volume. We can infer that the 2% change for the first firm is rational in the sense that all investors were acting as Bayesian investors. For the second firm, we can infer that the 2% change was less than rational, and therefore we will observe further adjustment in the form of a (stronger) post-announcement drift.

So, our empirical strategy is to identify the firms that have exhibited abnormally high trading volume after controlling for the magnitude of the price change and firm characteristics, and to see if these firms exhibit a stronger drift. Controlling for the firm characteristics is crucial in this context. In the world according to the model, we have to control for firm characteristics to control for different levels of α and Z. In addition, in reality, different firms may have different arbitrage capacities and trading costs just to name two distinguishing differences. For example, Karpoff (1987) shows that trading costs are one of the primary determinants of the level of trading volume. Lower trading costs will lead to a larger volume reaction to news. The most natural way of controlling for the price change and firm characteristics is to run a regression of volume on the variables we want to control for, and use the residual volume as our measure. Our regression specification will be developed in section 4.

3. Data and variables used in the study

3.1. Measure of surprise and drift

We obtain quarterly earnings announcement dates and earnings per share from COMPUSTAT for the period between 1988 and 1996, and retrieve data on daily returns, market capitalization, and daily trading volume (share turnover) from CRSP. CDA/Spectrum provides the data on the percentage of firms' shares held by institutions, and IBES data contain the number of analysts who have made a forecast for each firm's quarterly earnings. We confine our sample to NYSE/AMEX firms following the convention of the volume literature of not including NASDAQ firms.

We construct Standardized Unexpected Earnings (SUE) as a measure of surprise following Bernard and Thomas (1993). SUE is defined as

$$SUE_t = \frac{e_t - E_{t-1}(e_t)}{\sigma_{(e_t - E_{t-1}(e_t))}} \tag{10}$$

where e_t denotes earnings announced at time t, $E_{t-1}(e_t)$ is an expectation of those earnings as of time t-1, and σ denotes the historical standard deviation of the difference between quarterly earnings and their expectation.

We will simply set $E_{t-1}(e_t) = e_{t-4}$, earnings in the same quarter a year ago, based on the seasonal random walk. This measure of SUE assumes that investors expect this quarter's earnings to be the same as those of the same quarter last year. Bernard (1993) has shown that even this simplistic measure of SUE is related to stock price reactions.[9]

Another surprise measure we use for a robustness check is the cumulative abnormal return (CAR) over the three-day period surrounding an earnings announcement. First, we calculate size-matched abnormal return $r_{i,t}$ as in Bernard (1993) [10], and sum the abnormal returns over the three-day period surrounding an earnings announcement. Thus if a firm makes an announcement at 0, the three-day CAR (henceforth TDC) is calculated as the sum of abnormal returns of Day -1, 0 and 1.

$$\text{TDC}_i = \sum_{t=-1}^{1} r_{it} \tag{11}$$

This measure assumes that investors' surprise is well captured by price changes surrounding an earnings announcement.[11]

We define the post-announcement drift as the cumulative abnormal return (CAR) for each portfolio for a certain period of time after the announcement, excluding the 3 days surrounding the announcement. For example, a 30-day drift is $CAR_{31} - CAR_1$, where $CAR_T = \sum_{t=0}^{T} r_{it}$ and t=0 represents the announcement day[12].

Table 1 reports the descriptive statistics of our sample. As in previous studies, we can observe that there exists a post-announcement drift in the same direction as the price change in the announcement window, no matter which measure of surprise we use. Figure 1 presents the drift patterns in SUE quintiles and TDC quintiles. SUE quintiles are based on the cutoff points in the distribution of SUEs in the previous quarter. TDC quintiles are based on the cutoff points in the distribution of TDCs in the current quarter.

3.2. Calculating residual trading volume that captures ω

In this section, we carefully calculate residual trading volume that captures news characteristics ω. Ideally, residual trading volume should not be correlated with the magnitude of the price change and firm characteristics. In this case, the source of variation in residual trading volume would only come from the news characteristics.

We proceed in two steps. The first step is to control for normal trading volume outside event windows. Some firms are more actively traded than others. Some firms move more closely with the market than others. To capture the part of volume generated strictly by the arrival of news, we would like to control for differences in the intensity of trading activity during normal periods and for market-wide effects. The second step is to control for the part of the event trading volume that might be related to the magnitude of the price change and firm characteristics within the event windows. Different firms can have different levels of α and Z. We should control for this within the event window to purge the part of trading volume that is due to firm characteristics.

3.2.1. First step

As the first step, we try to control for the normal level of trading volume outside earnings announcement windows. For this purpose we try to obtain *market-adjusted* trading volume. We calculate market-adjusted trading volume as follows. First, we regress the firm's daily turnover (shares traded/shares outstanding) on the value-weighted market turnover in the year prior to the announcement.[13] Second, market-adjusted volume for a given day is calculated by subtracting the predicted volume using the regression from the actual volume.

$$TO_{itk} = \alpha_{i,t-1} + \beta_{i,t-1} MktTO_{tk} + V_{itk}$$

$$\begin{aligned} &TO_{itk} : \text{Turnover for firm } i \text{, in year } t \text{, day } k \\ &\alpha_{i,t-1}, \beta_{i,t-1} : \text{ Coefficient estimates of market model for firm } i \text{ in year } t\text{-1} \\ &MktTO_{tk} : \text{Value - weighted market turnover} \\ &V_{itk} : \text{Market - adjusted volume for firm } i \text{, in year } t \text{, day } k \end{aligned} \tag{12}$$

Third, we sum the abnormal volumes in the three-day window. Market-adjusted trading volume will be further refined in the next section to control for firm characteristics and absolute price changes within the earnings announcement windows.

3.2.2. Volume, price change and firm characteristics

Before we move to the second step, we describe in this section the characteristics of the reaction of market-adjusted volume to earnings announcement news. In Table 1, the market-adjusted trading volume reaction is much greater when the news is positive, while the magnitude of the price changes are similar in TDC quintiles 1 and 5. That is, when the magnitude of price changes is the same, volume reaction is greater when the price change is positive. This is consistent with previous studies (Karpoff 1987). This asymmetry in the volume-return relationship has been explained by the existence of short-sales constraints. When the news is negative, those who want to sell but are subject to short-sales constraints cannot participate in the market (Chen, Hong, and Stein 2000). So, short-sales constraints reduce the trading volume when the news is negative.

Short-sales constraints can be severe for smaller firms. To address this issue, Figure 2 reports the influence of firm size on market-adjusted volume reaction in each TDC quintile. For the firms in size decile 1, the market-adjusted volume generated in TDC quintile 1 is only a fourth of that in quintile 5. But this asymmetry gradually disappears as the firm size increases. In size decile 10, market-adjusted volume reaction in TDC quintiles 1 and 5 are fairly symmetric. Figure 3 reports the influence of institutional ownership on market-adjusted trading volume in SUE and TDC quintiles. The effect of institutional ownership seems to be similar to that of size.

As is clear in Figures 2 and 3, there clearly exists an asymmetry in the relationship between volume and explanatory variables (magnitude of price changes, firm characteristics) depending on whether the news is positive or negative. The trading volume when there is negative news is significantly lower than when there is positive news, and the effects of firm characteristics were significantly different, too. It should be noted that in cases of negative news, the existence of short-sales constraints may make our measure of volume a noisier signal of news characteristics that we intended to capture in the second step.

3.2.3. Second step

Now we estimate a cross-sectional regression of trading volume on the price change and firm characteristics to obtain a measure of residual trading volume that captures news characteristics. There are 34 quarters in our sample period. We estimate cross-sectional regressions for each quarter and report the means of each quarter's coefficient estimates, the t-statistics for the time-series of coefficient estimates, and the average of the adjusted R-squares.

Specification 1 is our benchmark regression of market-adjusted volume on the absolute value of the price change alone.[14] To this specification, we will add several more control variables that are supposed to capture firm characteristics. Our measure of the price change is the CAR over the three-day announcement period (TDC).

$$V_{ti} = \alpha_t + \beta_t \cdot \left|\Delta P_{ti}\right| + v_{ti}$$

V_{ti} : Market - adjusted volume for stock i in quarter t
$\left|\Delta P_{ti}\right|$: Absolute value of CAR over the announcement window
v_{ti} : Residual volume for stock i in quarter t

Table 2, Panel A (first row) reports the regressions results. First we estimate cross-sectional regressions for each quarter without conditioning on a TDC quintile (Panel A). To account for the possibility of a piecewise linear relationship between market-adjusted trading volume and TDC, we also estimate quarterly cross-sectional regressions for each TDC quintile (the first rows of Panel B and Panel C report regression results for quintiles 1 and 5). We have seen in the previous section that the relationship between volume and the explanatory variables differs depending on whether the news is positive or negative. Therefore, separate regressions by TDC quintiles seem a more appropriate way to calculate residual volume. In the following section where the relationship between residual volume and drift is reported, separate regressions by TDC quintiles will be used. However, the results do not change significantly when we use residual trading volume that is calculated using all TDC quintiles. In all Panels, the coefficient of the absolute value of TDC turns out to be positive and significant. Adjusted R-squares range from 4.9% to 7.8%.

Specifications 2-8 are the regressions of market-adjusted volume on price changes and other firm characteristics.

Specification 2 adds the price level in the regression.

[Specification 2]

$$V_{ti} = \alpha_t + \beta_{t1} \cdot |\Delta P_{ti}| + \beta_{t2} \cdot price_{ti} + v_{ti}$$

V_{ti} : Market - adjusted volume for stock i in quarter t
$|\Delta P_{ti}|$: Absolute value of CAR over the announcement window
$price_{ti}$: Log(1 + Stock Price)
v_{ti} : Residual volume for stock i in quarter t

The motivation for including the price level is to control for differences in transactions costs. If the price is higher, the bid-ask spread becomes smaller in terms of the percentage of price and this could lead to greater volume reaction. It turns out that this variable is positive and highly significant in all three Panels. The increase in the adjusted R-square is the most dramatic in the case of Panel B, which looks at the first TDC quintile (negative news). The adjusted R-square increases from 6.7% to 14.1%.

In specification 3, we include market capitalization (size) instead of the price level. It turns out that larger firms have more trading. This is not surprising since a strong positive correlation exists between size and price. However, the increase in the adjusted R-square is much smaller, relative to its increase from specification 1 to specification 2. To check the relative importance of the price level and size, we include both size and the price level in specification 4.

[Specification 4]

$$V_{ti} = \alpha_t + \beta_{t1} \cdot |\Delta P_{ti}| + \beta_{t2} \cdot price_{ti} + \beta_{t3} \cdot Size_{ti} + v_{ti}$$

V_{ti} : Market - adjusted volume for stock i in quarter t
$|\Delta P_{ti}|$: Absolute value of CAR over the announcement window
$\mathrm{Size}_{\mathrm{ti}}$: Log(Size)
$\mathrm{Price}_{\mathrm{ti}}$: Log(1 + Stock Price)
v_{ti} : Residual volume for stock i in quarter t

It is interesting to note that the adjusted R-square does not change much from that of specification 2 (an increase of 0.1% to 0.3%) even though the coefficient estimates for size are all significant. It is also interesting to note that the sign of coefficients of size changes in Panels A and C when both size and the price are included. It remains positive and marginally significant (t-statistic of 1.96) in the case of Panel B. Thus after controlling for trading cost by including the price level, the independent contribution of size could be negative.

In the next specification, we try to include institutional ownership and analyst coverage in our regressions. It is possible that institutional investors are a proxy for rational investors. It is also possible that analyst coverage affects the precision of pre-announcement information. Care is needed, though, when including analyst coverage and institutional ownership. It is known that the first size-quintile firms contain a number of firms with no analyst coverage (Hong, Lim and Stein, 2000) and no institutional ownership (Gompers and Metrick, 2000). This will bias the regression coefficients. Thus when we include analyst coverage and institutional ownership, we discard the first size-quintile. As a benchmark for the performance of specification 8, we re-estimate specification 4 without the first size-quintile (specification 4*).

[Specification 8]

$$V_{ti} = \alpha_t + \beta_{t1} \cdot |\Delta P_{ti}| + \beta_{t2} \cdot price_{ti} + \beta_{j3} \cdot Size_{ti} + \beta_{t4} \cdot IO_{ti} + \beta_{t5} \cdot An_{ti} + v_{ti}$$

V_{ti} : Market - adjusted volume for stock i in quarter t
$|\Delta P_{ti}|$: Absolute value of CAR over the announcement window
$price_{ti}$: Log(1 + Stock Price)
$Size_{ti}$: Log(Size)
IO_{ti} : Log(1 + Percentage held by institutional investors)
An_{ti} : Log(1 + Number of analysts following the stock)
v_{ti} : Residual volume for stock i in quarter t

The adjusted R-square significantly increases when small firms are excluded in both specifications 4* and 8. However, the levels of the adjusted R-square are basically the same between specification 4* and specification 8 even though the added firm characteristics, i.e., institutional ownership and analyst coverage, have significant coefficient estimates.

We also estimate regressions for all specifications using raw trading volume instead of market-adjusted trading volume. The basic results of Table 2 remain. In fact, whatever specification we use for our residual trading volume measure, the main empirical results of the paper change very little.

Our model's implication is that trading volume after controlling for the price change and firm characteristics is related to the post-announcement drift. Thus ideally, residual volume should not be correlated with the magnitude of the price change and firm characteristics. Table 3 shows how well our regression specification controls for the price change and firm characteristics. We form low/medium/high residual volume groups for each TDC quintile and check whether residual trading volume is independent of other firm characteristics and price changes. We can see that two residual-volume groups (low and high) exhibit similar initial price reactions and firm characteristics, under all the specifications used, while displaying a good spread in the market-adjusted volumes.

Figure 4 reports the means of the residual volume calculated using specification 4 in 50 cells sorted by size deciles and TDC quintiles. The results for the other specifications are basically similar to those in this figure. In Figure 4, we can see that no visible pattern exists in the relationship between residual volume and the initial price change or size. We conclude that our residual volume measure calculated using cross-sectional regressions has the desired property of no correlation with the initial price change and firm characteristics, and that the differences in the drift between the high/low residual-volume groups will well reflect the pure volume effect.

4. Empirical findings

4.1. Residual trading volume and drift patterns

Table 4 presents the relationship between residual volume calculated using specification 2 (control variables: price change, log price) and the drift. We report drift over 60 and 170 days after the announcement period. Table 4 shows the relationship between residual volume and the drift in each SUE quintile. We also use our second measure of surprise, which is TDC .

We find very strong evidence in support of our model's prediction in the case of positive news regardless of what surprise measure or what specification we use. High residual trading volume firms exhibit a stronger drift than low residual trading volume firms.

The results are much weaker when there is negative news. The results are somewhat mixed depending on which surprise measure or horizon we use. In any case, we find stronger results at the extreme quintiles, namely quintiles 1 and 5. This is not surprising given Figure 2. The magnitude of market-adjusted trading volume is much greater in the cases of these two quintiles compared to the other quintiles. Thus residual trading volume can have more meaningful variation in these two quintiles.

Figure 5 clearly shows the drift patterns of high and low residual trading volume for the first and fifth SUE and TDC quintiles. Regardless of which surprise measure we use, quintile 5 (positive news) shows a clear drift pattern that depends on the magnitude of residual trading volume. In the case of negative news, the drift pattern is consistent with our model's prediction when we use the SUE measure but the difference becomes insignificant in the case of the TDC measure.

In SUE quintile 5, the high residual-volume group exhibits a significantly higher drift than the low residual-volume group over all the horizons used. For Drift60, the drift for a high residual-volume firm is 2.1% while that of a low residual-volume firm is 0.33%. The difference between the two is significant (t-statistic[15] of 5.67). A similar result is obtained at a longer horizon (Drift170: 2.23% vs. 0.62%, t-statistic for the difference of the two is 2.47). The same pattern is observed in SUE quintile 4. For Drift60, the drift for a high residual-volume firm is 1.32% while that of a low residual-volume firm is –0.26%. The difference between the two is significant (t-statistic of 5.19). A similar result is found at a longer horizon (Drift170: 1.46% vs. -0.25%, t-statistic of 2.68). It is very interesting to note that for the firms with positive news, the drift for low residual-volume stocks is very weak. In the case of low residual-volume stocks, in the fifth SUE quintile, the drift over 60 days is only 0.33%. The drift even becomes negative (though not individually significant) for the fourth SUE quintile. This implies that the unconditional drift we observe in Figure 1 is mainly driven by high residual-volume firms. The basic results still hold even when we use TDC as our surprise measure. In TDC quintile 5, the high residual-volume group exhibits a significantly higher drift over all the horizons reported.

In SUE quintile 1, the difference in the drifts between the two residual-volume groups is insignificant over the 60-day horizon, but the magnitude of the drift over 170 days is significantly higher for the high residual-volume group (-4.71% vs. -3.17%, t-statistic of 2.12). However, we are cautious in concluding that our model's prediction also survives in the case of negative news since the relationship between residual volume and the drift disappears when we use a different surprise measure, i.e., TDC. In TDC quintile 1, there does not exist any statistically significant difference in drift patterns between large and small residual trading volume firms. We will discuss the possible explanation for the weak evidence in the case of negative news in section 4.3.

We also check whether we can get similar results for different specifications. Figure 6 reports the drift pattern when we calculate residual trading volume using specification 4. The pattern is almost identical to that of specification 2. We also report the results for specification 8 where we include all the variables we consider in this paper. Here, when we calculate residual trading volume, we discard the first size-quintile. Table 5 shows the results under specification 8 for both surprise measures. The results of the previous specifications still hold. When positive news arrives (SUE quintiles 4 and 5, or TDC quintiles 4 and 5), the high residual-volume stocks exhibit a significantly higher drift than the low residual-volume stocks. However, when there is negative news, the differences in the drifts between the residual volume groups become insignificant at long horizons.

We have seen that the effect of high residual volume is to significantly increase the magnitude of the drift when there is positive news. For positive-news stocks (quintile 5), the effect of residual volume seems quite long-lived regardless of what surprise measure or specification we use. The difference in the drifts between high and low residual-volume stocks persists even up to 170 trading days after the announcement.

4.2. The magnitude of initial price reaction and residual trading volume

In this section, we further investigate the implication of the model. Our model suggests that trading volume contains information about how much initial price reaction differs from that of rational level. By looking at price change alone, we cannot identify whether the price reaction around earnings announcement fully reflects the information contained in the announcement or not. However, according to our theory, if a price change is accompanied by large trading volume this is the case where price does not fully reflect the information. In this case, we should expect stronger drift. We examine this implication of the model in this section.

First, we test whether average reaction of price to earnings announcement is different depending on the magnitude of residual trading volume. Our model predicts that on average price reaction to a given SUE should be smaller for the group of firms that experience high residual trading volume. To test this hypothesis we run the following regression for the pooled sample.

$$TDC_{it} = \alpha + [\beta_1 + \beta_2 V_{it}] SUE_{it} + \varepsilon_{it}$$

where *i* denotes firm and *t* denotes the quarter when the announcement took place. Our results are robust to whatever residual trading volume measure we use and we only report the result where residual trading volume from specification 4 is used. If our model's prediction is correct, we should have negative sign for β_2 since high residual trading volume deters fully rational price reaction to the information. Also we run the following regression.

$$Drift_{it} = \alpha + [\gamma_1 + \gamma_2 V_{it}] SUE_{it} + \varepsilon_{it}$$

Now dependent variable is our 60-day drift measure[16] that does not include the price change within the three-day window around earnings announcement. In this case we expect to have positive γ_2 since stocks with high residual trading volume should exhibit stronger drift. Table 6 reports the results. Panel A reports the coefficient estimates and t-statistics when we use TDC as dependent variable. As expected the sign of β_2 is negative and significant. Panel B reports the results when we use drift measure as dependent variable. In this case γ_2 is positive and significant, which is consistent with the model's prediction.

To check the robustness of the results we run following quarterly regressions for low and high residual-volume samples for each quarter.

$$TDC_{it} = \alpha + \beta_1 SUE_{it} + \varepsilon_{it}$$

$$Drift_{it} = \alpha + \gamma_1 SUE_{it} + \varepsilon_{it}$$

Thus we will have 34 coefficient estimates of β_1 and γ_1 for each low and high residual-volume sample. First, we test whether the means of β_1 are significantly different between low and high residual-volume samples. Panel C shows that the mean of β_1's for low residual-volume sample is significantly larger than that of high residual-volume sample. Panel D reports the regression results when we use 60-day drift as the dependent variable. In this case, the mean of γ_1 for high residual-volume sample is significantly larger than that of low residual-volume sample as expected.

4.3. Asymmetry in informativeness of residual volume between positive and negative news

We have seen that our model's prediction is strongly supported when positive news is announced. However, when there is negative news, trading volume seems to have only a weak, or insignificant, effect on the drift. We think that this weak effect of volume on the drift is due to short-sales constraints. Our model assumes that when negative news is announced, the price fails to fall to the rational level because of the underreacting investors, and the rational investors sell to underreacting investors to take advantage of their underreaction. However, it is not easy to sell stocks short when stock prices are declining since short sales are possible only after an uptick. As we have seen in Figure 2, (market-adjusted) volume is much smaller in cases of negative news than in cases of positive news and we believe this is partly due to the existence of short-sales constraints. Karpoff (1987) also offers a similar argument to explain the asymmetric nature of trading volume. In addition, some institutional investors, such as mutual funds, take short positions rarely, if ever. If some investors do not participate in trading upon receiving negative news, (residual) trading volume can only be a very noisy signal about the news characteristics we are trying to capture. Low residual volume may be just a sign of strong short-sales constraints, not of consensus among investors. A recent paper by Chen, Hong, and Stein (2001) corroborates our interpretation. They explicitly model short-sales constraints and show that due to the existence of short-sales constraints, pessimists' opinions are not fully reflected in stock prices. If pessimists are not active in trading activities, little trading volume would be generated in the case of negative news. Diamond and Verrecchia (1987) also make a similar prediction. In fact, if we look at

Figure 5, the drift is more persistent in the case of negative news than in the case of positive news, suggesting negative news is incorporated into stock prices more slowly.

Our empirical results strongly suggest that the informativeness of trading volume for the subsequent drift is asymmetric, and future research on this asymmetry can be fruitful.

4.4. Residual trading volume, size, and institutional ownership

In this section, we further investigate whether the signal that is generated from residual trading volume has different implications for the drift depending on firm size and institutional ownership. The focus of our research so far has been to check whether trading volume can generate additional information after controlling for price changes and firm characteristics. However, some might argue that if large trading volume reflects the activity of arbitrageurs after public announcements, large trading volume may decrease the magnitude of the drift, by propagating information quickly. Suppose we look at firms with greater arbitrage capacity. Usually, these firms are considered to be large and to have more institutional holdings. If the arbitrage argument is correct, a high trading volume for these firms should reflect the behavior of arbitrageurs and information incorporation should be quicker.

However, our model's implication is quite different. Even if many arbitrageurs are holding the stock, high trading volume can be observed only when there are underreacting investors with whom they can trade. Trading volume will be higher when the degree of underreaction is high. Thus even when a firm is large or mostly held by institutions, high residual volume should imply a stronger drift than low residual volume.

To address this issue, we look at the magnitude of the drift of low and high residual trading volume stocks for each size and institutional ownership tertile. Tables 7 and 8 report the results. Here we use specification 4 in calculating residual trading volume but the results are basically the same when we use different specifications.

Table 7 first reports the results for institutional ownership (henceforth IO) tertiles. Panel A reports Drift170 for each IO tertile without controlling for volume. Interestingly, for positive news, the magnitude of the drift is not monotone with respect to IO. Panel B reports the results when we condition on residual trading volume. In the case of positive news, the drift is stronger in the case of large trading volume regardless of the level of institutional ownership and the difference is strongest in the third IO tertile. For example, in the case of positive news, Drift170 of the third IO tertile with large trading volume is 2.5%, which is higher than that of low residual volume by 1.6% and statistically significant. We obtain stronger results if we use TDC as our surprise measure. The difference now becomes 3.82% and the t-statistic is 4.11. The results are insignificant in the case of negative news.

Basically, the same pattern is observed if we divide our sample by firm size instead of IO (Table 8). In the case of the third size tertile with positive news, firms with larger residual trading volume exhibit a stronger drift.

We conclude that even among firms for which a high level of arbitrage activity is anticipated, high residual-volume stocks tend to exhibit a stronger drift, which is consistent with our model's prediction.

5. Conclusion

Investors' underreaction to earnings announcements has led many researchers to investigate possible explanations for it. We contribute to this field by looking at trading volume around earnings announcements and its implications for the magnitude of the post-announcement drift. Our model mirrors recent behavioral models. For example, BSV (1998) and DHS (1998) analyze stock price reactions when investors put a lower weight on public news than rational Bayesian investors would. HS (1999) predict that when public news leaves a lot of room for private interpretation, there would be higher trading volume and a stronger subsequent drift.

In this paper, we show that public news that has clear value implications will lead to lower trading volume and a smaller drift. We show that trading volume generated by the announcement of public information can be a result of the interaction between two different types of investors, and that the magnitude of trading volume can give information about the degree of underreaction by investors subject to the conservatism bias. We show that the degree of underreaction depends on news characteristics. If the information content of the news is clear and salient, as in the case of a takeover bid at a certain price, there would be no room for underreaction and no trading volume would be observed. Therefore trading volume will be high when the information content of the earnings news is not clear or the saliency of the news is weak.

In our model, ω captures the saliency of the news. If the news is salient enough (ω=1), every investor behaves as if he were a Bayesian investor and there will not be any trading volume, and only the price will adjust. However, if the content of the news is not clear or the saliency of the news is weak, underreacting investors put irrationally low weight on the news and the price does not fully reflect the information contained in the earnings report.

In our model, it is shown that trading volume is negatively related to ω. Thus we argue that trading volume can actually convey information in addition to the information stock returns alone can convey. After a certain level of initial price reaction to news is observed, trading volume can give additional information about the magnitude of further price adjustments.

In the empirical part of the paper, we carefully control normal trading volume that can be related to firm characteristics and the magnitude of price changes, because we are only interested in the part of the volume related to the news characteristics. We find supportive evidence for the model in cases of positive news. Higher trading volume after controlling for price changes and firm characteristics suggests a stronger drift. The result is very robust to the many specifications that we use to calculate abnormal trading volume and to different surprise measures. In cases of negative news, we find no systematic relationship between trading volume and subsequent returns. One possible explanation for the weak evidence for the case of negative news can be found in institutional arrangements such as short-sales constraints. When there is negative news and the initial price reaction is less than the rational level, the rational investors, who are aware of the mispricing, cannot take advantage of it when there are short-sales constraints. Therefore, low residual volume in the case of negative news might not generate strong signals about the degree of investors' disagreement due to additional noise.

We hope our study opens some possibilities for future research as well. Theoretically, one could explicitly model the short-sales constraints in our model. There have been recent developments in this field in relation to private information (For example, Chen, Hong, and Stein (2000); an earlier example is Diamond and Verrecchia (1987)). Empirically, one can check whether the asymmetric results we find in this paper can also be found in other events such as dividend omissions and initiations. In this case, however, one should be concerned about the relatively small size of samples when compared to earnings announcements.

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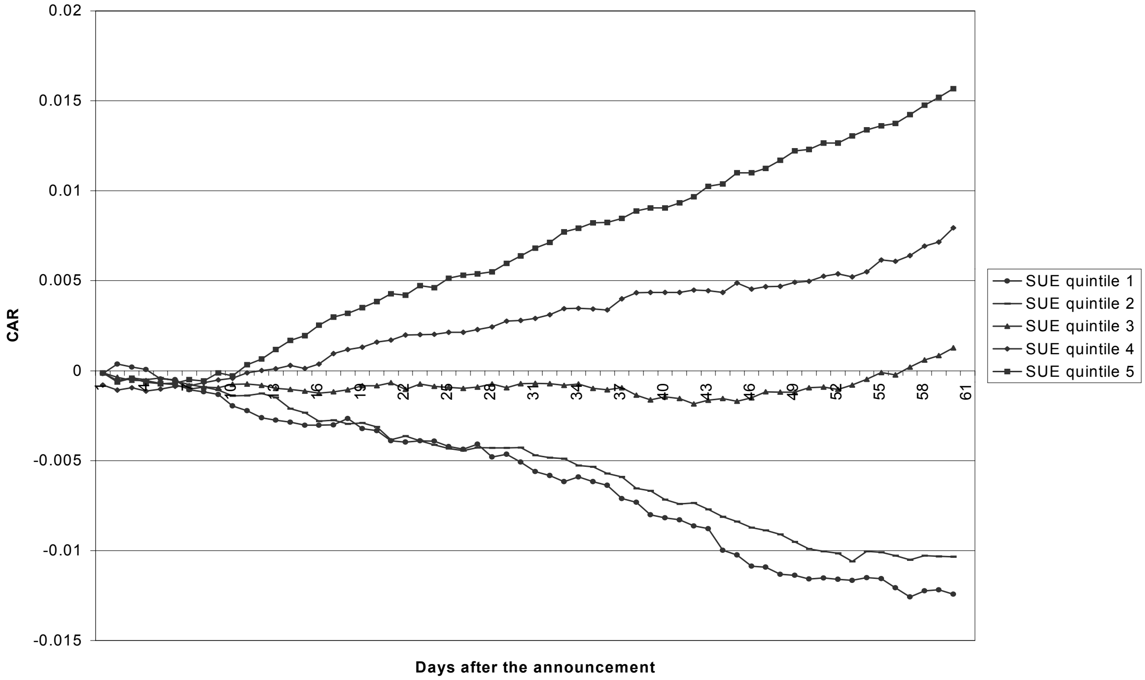
Figure 1. Post-announcement drift in SUE/TDC quintiles

Post-announcement drift is measured as the cumulative abnormal return (CAR) after the three-day event period surrounding the announcement. SUE (Standardized Unexpected Earnings) quintiles are based on the cutoff points in the distribution of SUEs in the previous quarter. SUEs are based on the random walk expectation. TDC quintiles are based on the cutoff points in the current quarter in the distribution of the three-day cumulative abnormal return during the event period.

A. Post-announcement drift in SUE quintiles



B. Post-announcement drift in TDC quintiles

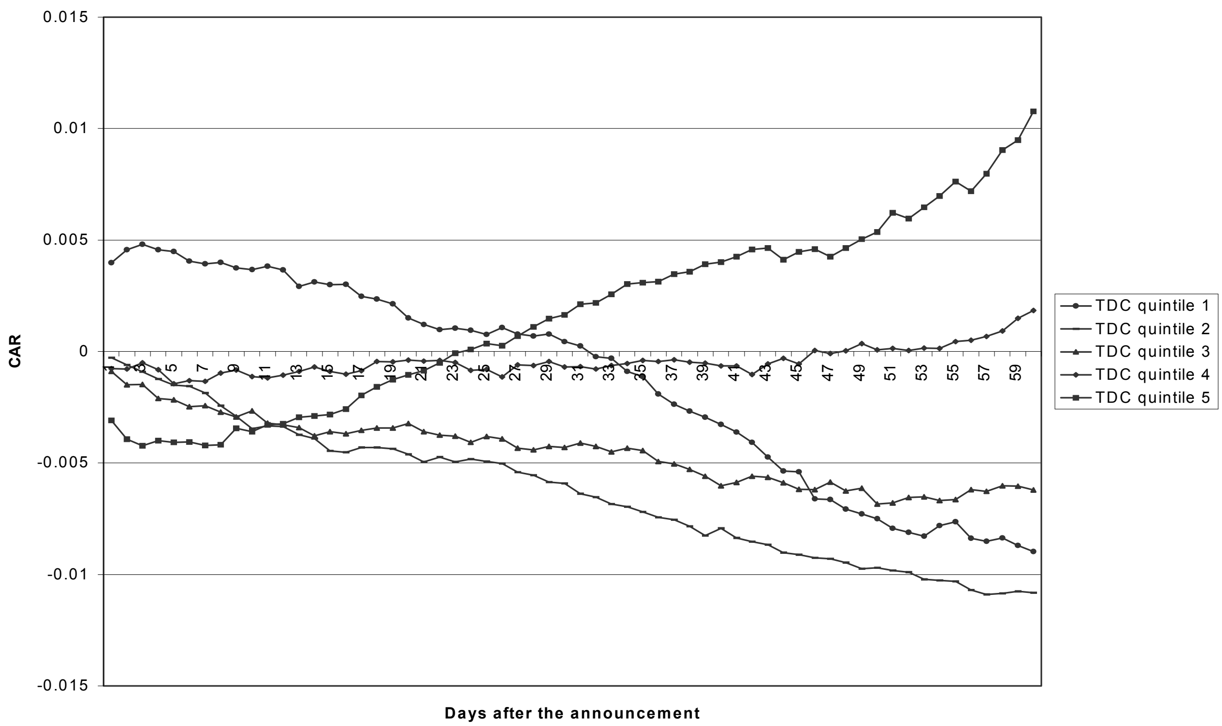
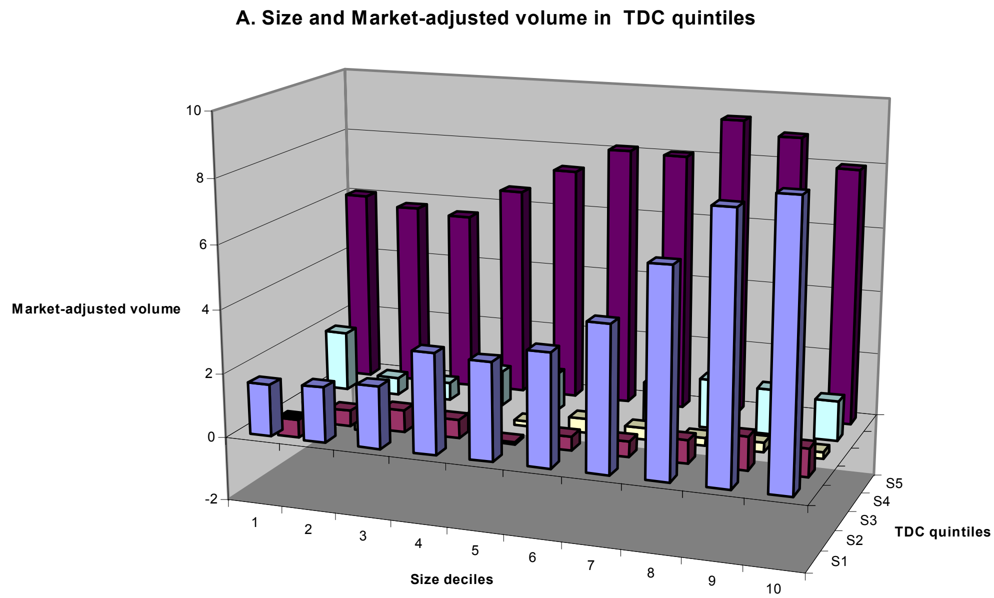


Figure 2. Size and volume reaction to earnings news

Panel A reports the market-adjusted volume during the three-day period surrounding the announcement in 50 cells sorted by size decile and TDC quintile. TDC quintiles are based on the current quarter distribution of the cumulative abnormal returns during the event period. Size deciles are based on the distribution of market capitalizations at the beginning of the quarter in which the earnings news is announced. Panel B reports the raw turnover in the 50 cells sorted in the same way.



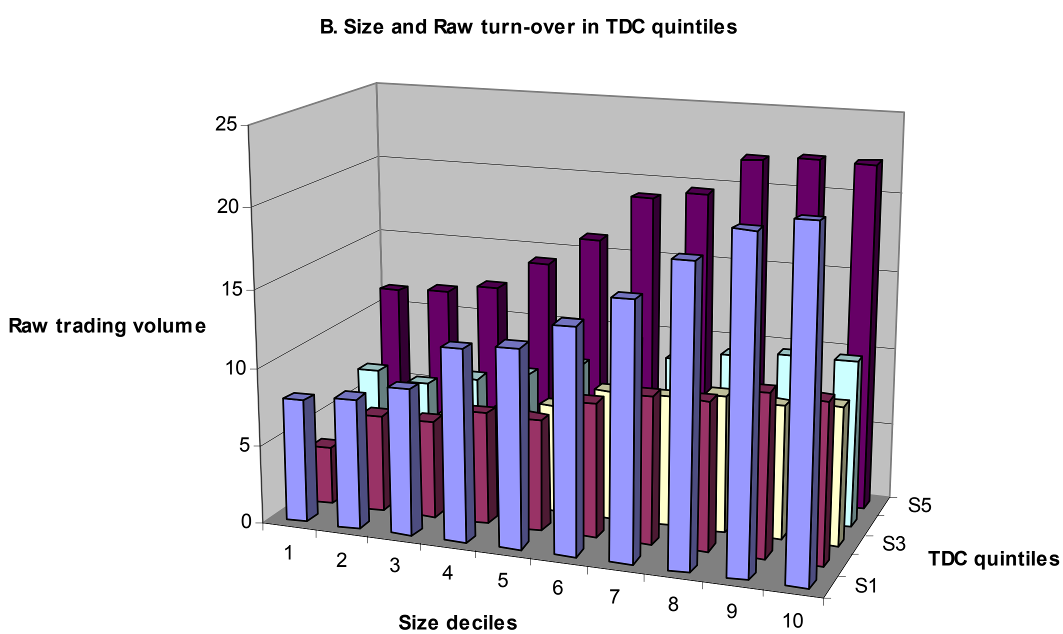
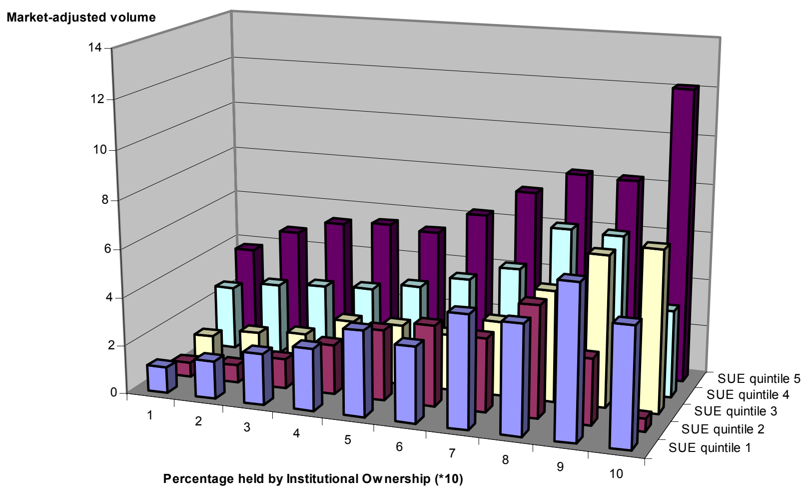


Figure 3. Institutional ownership and volume reaction to earnings news

Panel A reports the market-adjusted volume during the three-day period surrounding the announcement in 50 cells sorted by institutional ownership and SUE. Percentage held by institutions is measured at the beginning of the quarter in which the earnings news is announced. Panel B reports the market-adjusted volume in 50 cells sorted by institutional holdings and TDC. TDC quintiles are based on the current quarter distribution of the cumulative abnormal returns during the three-day event period.

A. Institutional Ownership and Market-adjusted Volume in SUE quintiles



B. Institutional Ownership and Market-adjusted Volume in TDC quintiles

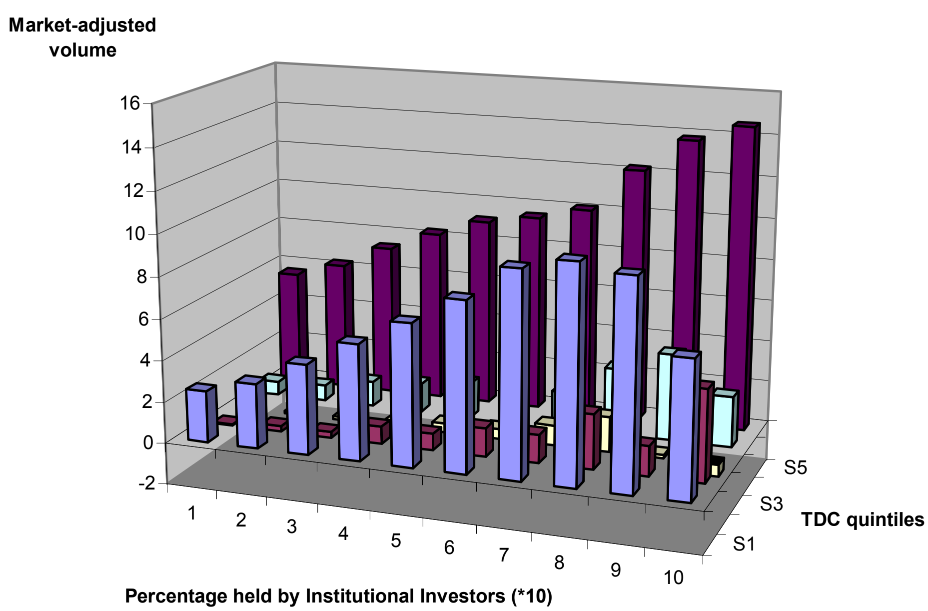


Figure 4. Residual volume and size , initial price reaction to earnings news
Residual volume is calculated as the residuals from the specification 4 regressions estimated each quarter in each TDC quintile separately. In specification 4, control variables are the cumulative abnormal return over the three-day event period, log(size), and log(1+lagged price). Means of the residual volume in 50 cells sorted by size decile and TDC quintile are reported.

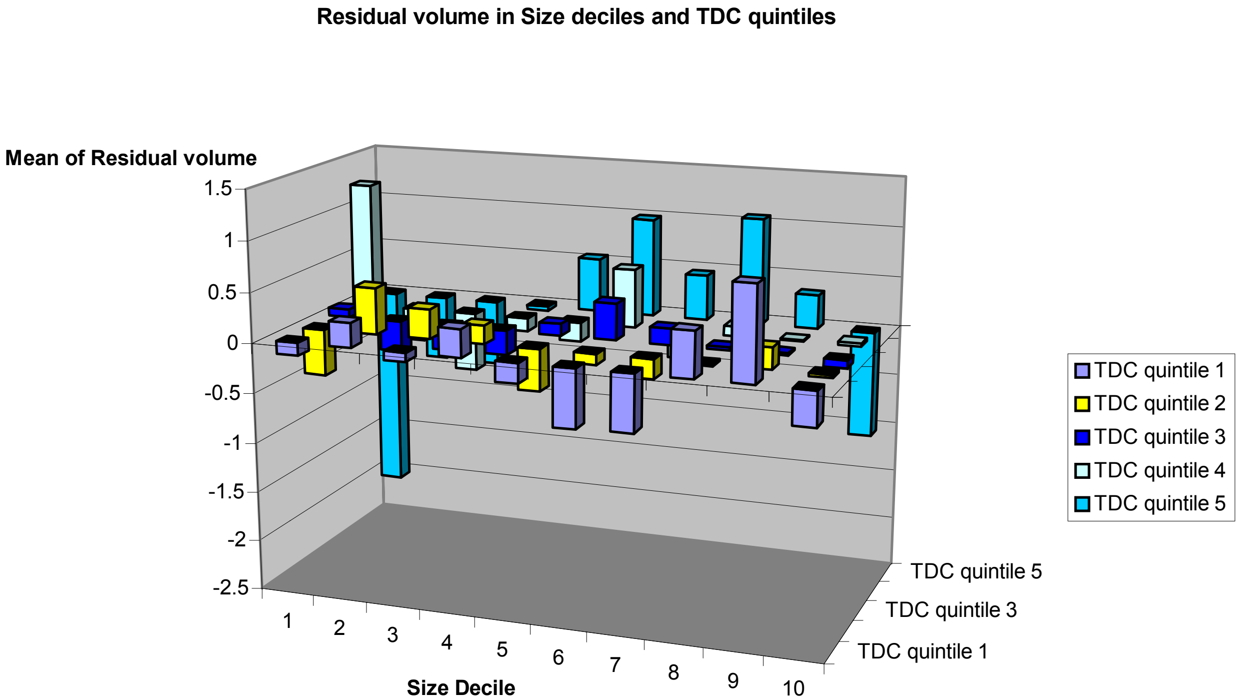
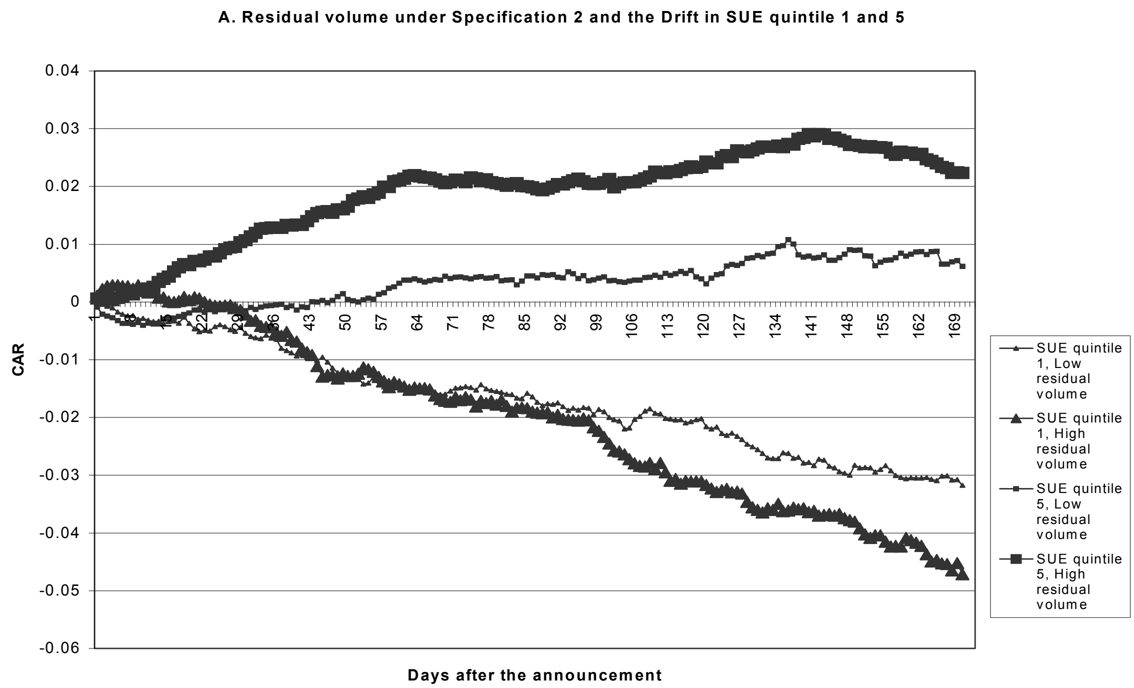


Figure 5. Residual volume under Specification 2 and the drift

Residual volume is calculated as the residuals from the specification 2 regressions estimated each quarter in each TDC quintile separately. In specification 2, control variables are the absolute value of the three-day cumulative abnormal return and log(1+lagged price). ($V_{tji} = \alpha_{tj} + \beta_{tj1} \cdot |\Delta P_{tji}| + \beta_{tj2} \cdot Price_{tji} + v_{tji}$) Observations in each TDC quintile each quarter are divided into three equal-sized groups (low-medium-high) depending on the residual volume. We report the 170-day drift defined as the CAR after the announcement period in high/low residual volume groups for SUE/TDC quintiles 1 and 5. Bigger dots represent a high residual volume group.



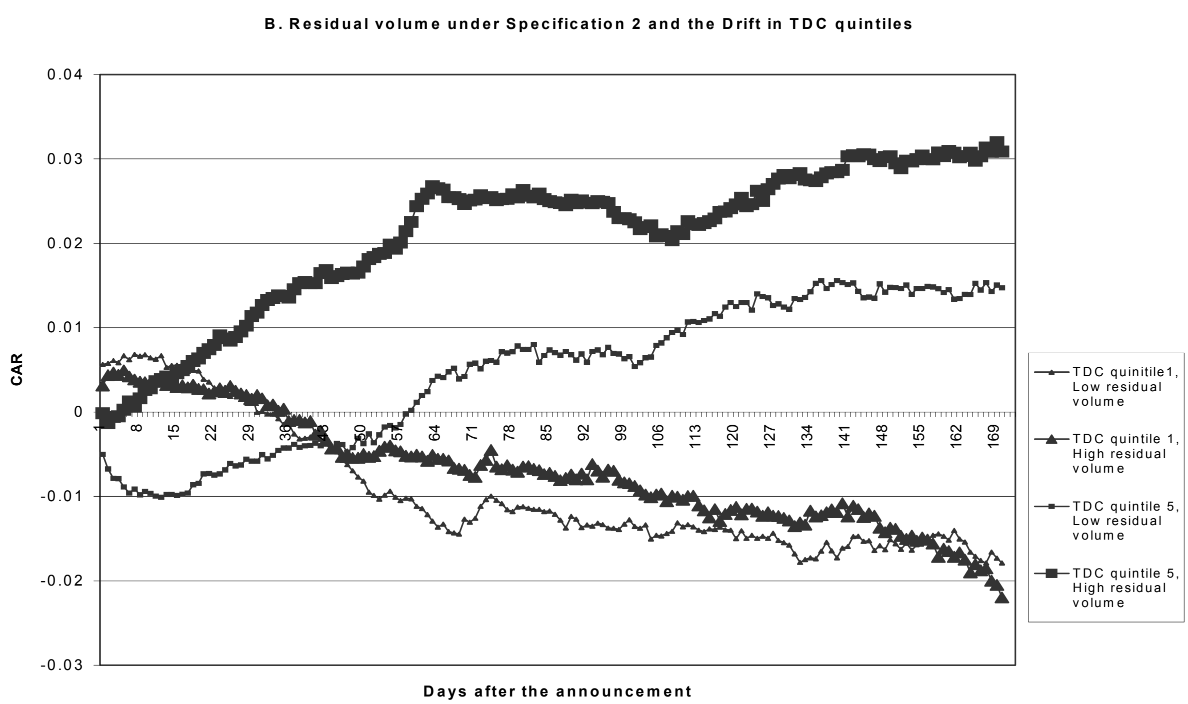
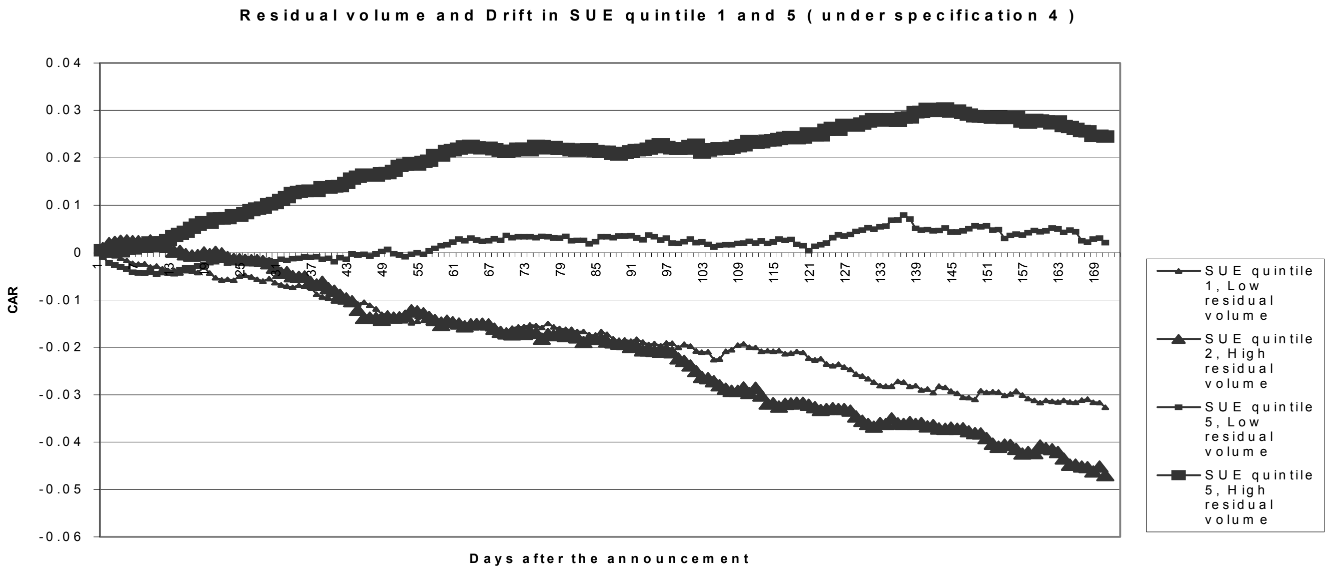


Figure 6. Residual volume under Specification 4 and the drift

Residual volume is calculated as the residuals from the specification 4 regressions estimated each quarter in each TDC quintile separately. In specification 4, control variables are the absolute value of the three-day cumulative abnormal return, log(size) and log(1+lagged price). ($V_{tji} = \alpha_{tj} + \beta_{tj1} \cdot \left|\Delta P_{tji}\right| + \beta_{tj2} \cdot Price_{tji} + \beta_{tj3} \cdot Size_{tji} + v_{tji}$) Observations in each TDC quintile each quarter are divided into three equal-sized groups (low-medium-high) depending on the residual volume. We report the 170-day drift defined as the CAR after the announcement period in high/low residual volume groups for SUE/TDC quintiles 1 and 5. Bigger dots represent a high residual volume group.



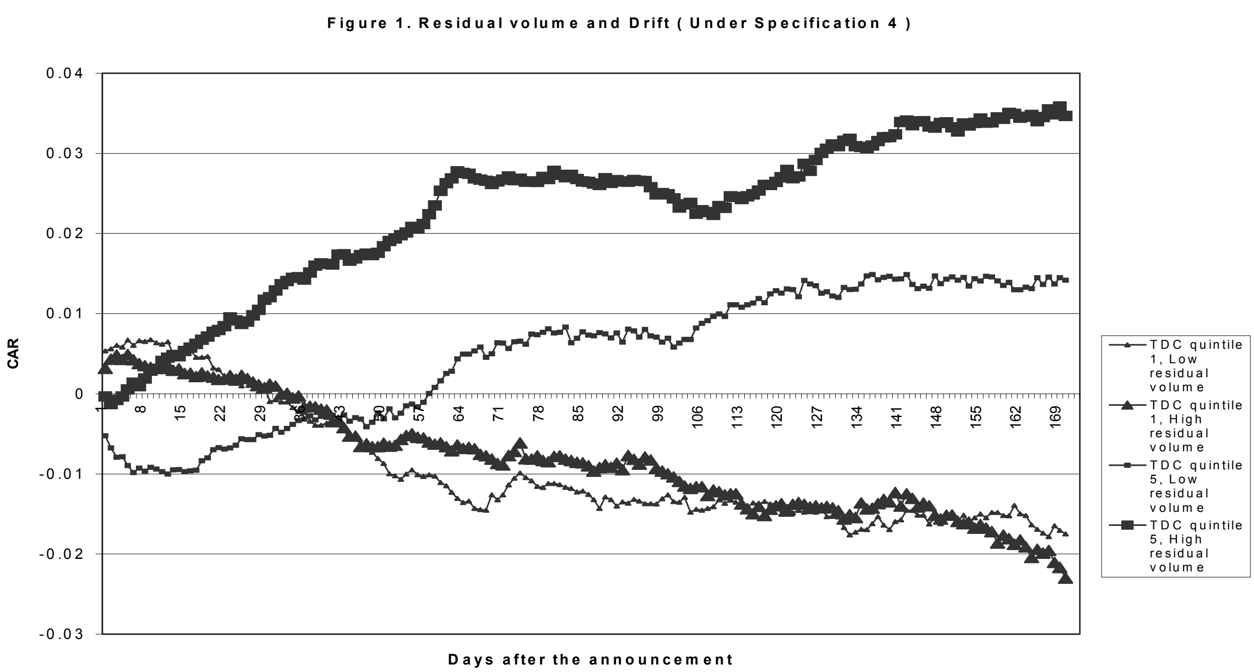
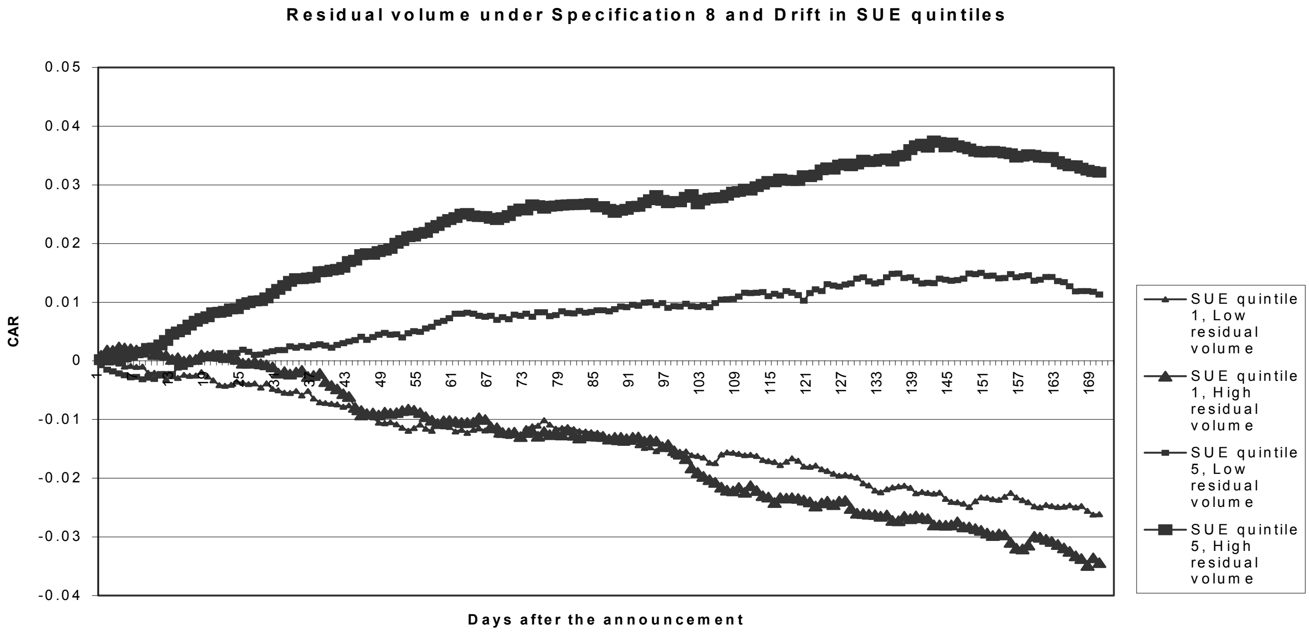


Figure 7. Residual volume under Specification 8 and the drift

Residual volume is calculated as the residuals from the specification 8 regressions estimated in each quarter in each TDC quintile separately. In specification 8, control variables are the absolute value of the three-day cumulative abnormal return, log(size), log(1+institutional ownership), log(1+analyst coverage), and log(1+lagged price). ($V_{tji} = \alpha_{tj} + \beta_{tj1} \cdot |\Delta P_{tji}| + \beta_{tj2} \cdot \mathrm{Price}_{tji} + \beta_{tj3} \cdot Size_{tji} + \beta_{tj4} \cdot IO_{tji} + \beta_{tj5} \cdot An_{tji} + v_{tji}$) Observations in each TDC quintile each quarter are divided into three equal-sized groups (low-medium-high) depending on the residual volume. We report the 170-day drift defined as the CAR after the announcement period in high/low residual volume groups for SUE/TDC quintiles 1 and 5. Bigger dots represent a high residual volume group.



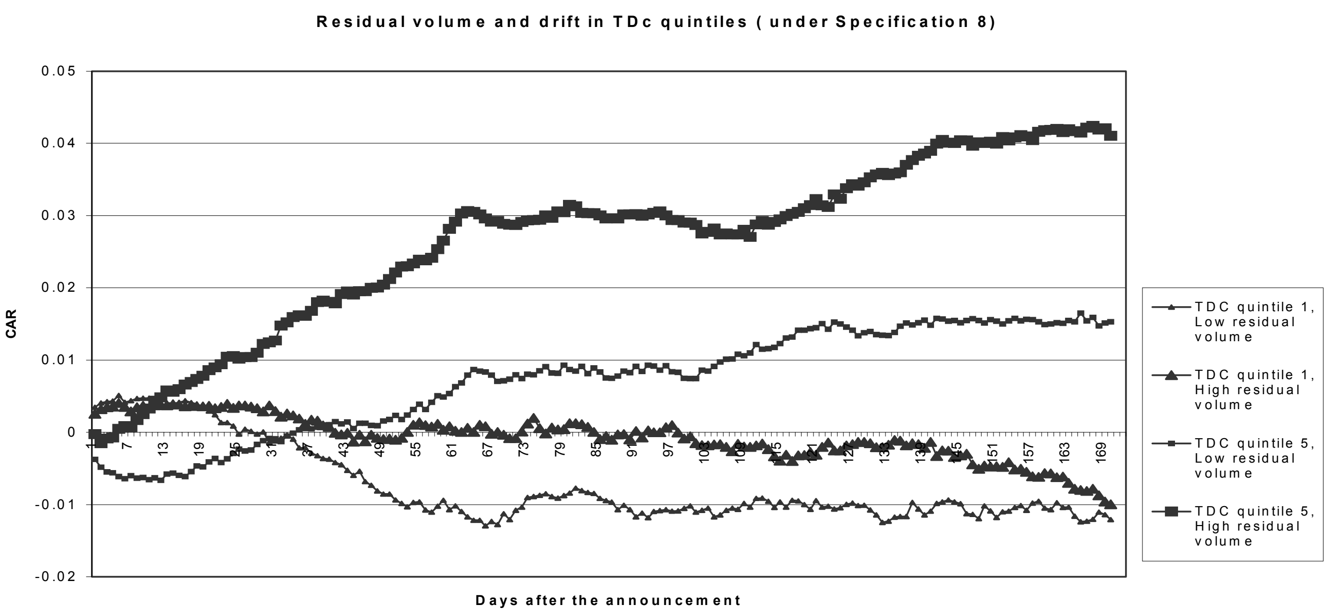


Table 1. Descriptive statistics

Descriptive statistics of firms that made earnings announcements between 1988 and 1996. TDC is calculated as the three-day sum of daily size-matched abnormal returns surrounding earnings announcements. For example, if a firm makes an announcement at t, the TDC is the sum of daily abnormal returns for t-1,t,and t+1. Drift60 is the sum of 60 daily size-matched abnormal returns outside of the earnings announcement window. For example, if a firm makes an earnings announcement at t, Drift60 is the sum of daily abnormal returns starting from t+2 and ending on t+63. Three-day volume is the sum of daily share turnover surrounding earnings announcements. Market-adjusted volume is calculated as follows. We estimate firm level regressions with daily share turnover as a dependent variable and value-weighted market turnover and a constant as independent variables for each year. In the following regression, *i* is a firm indicator, *t* is for trading days and *T* for year. $vol^i_{t,T} = \alpha^i_{t,T} + \beta^i_{t,T} mkt^i_{t,T} + \varepsilon^i_{t,T}$

Three-day market adjusted trading volume is the sum of residuals in the above equation during the three-day period surrounding earnings announcement.

A. SUE quintile

	Obs	TDC	Drift60	3 day volume (%)	3 dayMarket Adjusted Volume (%)
1st quintile	16492	-1.34	-1.64	1.24	0.233
(t-stat)		(-23.89)	(-12.02)		
2nd quintile	17871	-0.79	-1.26	1.07	0.168
(t-stat)		(-16.00)	(-10.05)		
3rd quintile	20854	0.30	-0.21	1.02	0.197
(t-stat)		(6.91)	(-1.87)		
4th quintile	17661	1.34	0.52	1.22	0.348
(t-stat)		(24.34)	(4.26)		
5th quintile	16993	1.79	1.21	1.50	0.532
(t-stat)		(29.36)	(9.41)		
5th-1st		3.12	2.85		0.299
(t-stat)		(37.79)	(15.20)		(19.74)

B. TDC Quintile

	Obs	TDC	Drift60-CAR	3 day volume (%)	3 day Market Adjusted Volume (%)
1st quintile	17942	-7.89	-0.91	1.52	0.478
(t-stat)		(-193.81)	(-6.31)		
2nd quintile	17942	-2.00	-1.09	0.9	0.066
(t-stat)		(-330.47)	(-9.62)		
3rd quintile	17942	0.006	-0.62	0.78	0.013
(t-stat)		(1.61)	(-5.60)		
4th quintile	17942	2.13	0.18	0.98	0.131
(t-stat)		(326.83)	(1.67)		
5th quintile	18103	9.02	1.08	1.82	0.764
(t-stat)		(142.67)	(7.62)		
5th-1st		16.91	1.99		0.286
(t-stat)		(224.88)	(9.85)		(17.21)

Table 2. Calculating residual trading around earnings announcements using market-adjusted trading volumes

This table shows the results of the regressions for calculating residual trading volume. Residual volume is supposed to capture the magnitude of trading volume that is generated due to news characteristics after controlling for (absolute) price changes. In every specification, three-day market-adjusted trading volume is an independent variable of regressions. We collect data for firms that made earnings announcements for each quarter and estimate quarterly cross-sectional regressions. |TDC| is the absolute value of the three-day sum of daily size-matched abnormal returns surrounding earnings announcements. P is share price and we take its log. Log(size) is the log of market capitalization at the end of the previous quarter. Institutional ownership data are from CDA/Spectrum and represent the percentage of firms' shares held by institutions. Analyst coverage is obtained from IBES consensus data. When a firm is not covered by CDA/Spectrunm or IBES, we assign 0s to institutional ownership holding and analyst coverage. The results without this restriction are not affected much. Spec4*, spec5*,spec6*, spec7* and spec8* discard the first size-quintile since we have many firms with 0 institutional ownership and no analyst coverage. Panel A represents regression results using the full sample. We report parameter estimates, t statistics and an adjusted R-square.

We also estimate quarterly regressions for each TDC quintile to address possible concerns of piecewise linear relationships between |TDC| and market-adjusted volume. Here we only report the results for the first and fifth TDC quintiles but the basic results are the same for other TDC quintiles.

A. Full Sample

	|TDC|	log(size)	log(1+ i.o)	log(1+an)	log(1+P)	adjusted R2(%)
spec1	65.11					7.8
	(17.82)					
spec2	75.3				1.95	9.9
	(19.78)				(19.15)	
spec3	70.44	0.58				8.9
	(18.91)	(12.59)				
spec4	75.15	-0.3			2.47	10
	(19.73)	(-5.78)			(25.05)	
spec4*	99.57	-0.3			2.52	12.0
	(23.59)	(-5.57)			(22.43)	
spec5*	98.85		0.40		1.80	12.1
	(23.79)		(10.91)		(14.09)	
spec6*	98.66	-0.34	0.42		2.33	12.2
	(23.81)	(-6.67)	(11.36)		(19.63)	
spec7*	98.33	-0.60		0.93	2.49	12.4
	(23.40)	(-9.54)		(12.67)	(21.90)	
spec8*	97.97	-0.58	0.22	0.79	2.41	12.4
	(23.65)	(-9.49)	(5.33)	(10.61)	(19.71)	

B. Fist TDC Quintile

	|TDC|	log(size)	log(1+ i.o)	Log(1+an)	log(1+P)	adjusted R2
spec1	73.51					6.7
	(16.47)					
spec2	96.44				4.63	14.1
	(20.86)				(28.22)	
spec3	89.74	1.85				11.9
	(19.89)	(25.12)				
spec4	96.48	0.22			4.25	14.2
	(20.84)	(1.96)			(16.74)	
spec4*	121.50	0.29			4.41	16.2
	(22.36)	(2.31)			(16.55)	
spec5*	120.95		0.50		4.53	16.2
	(22.27)		(6.21)		(24.85)	
spec6*	120.97	0.25	0.49		4.14	16.3
	(22.22)	(2.05)	(6.30)		(15.40)	
spec7*	120.14	-0.15		1.35	4.30	16.6
	(22.20)	(-1.12)		(7.64)	(16.35)	
spec8*	120.01	-0.14	0.20	1.25	4.22	17.5
	(22.13)	(-1.04)	(2.12)	(6.29)	(15.54)	

C. Fifth TDC Quintile

	|TDC|	log(size)	log(1+ i.o)	Log(1+an)	log(1+P)	adjusted R2
spec1	49.29					4.9
	(9.89)					
spec2	65.50				3.62	9.0
	(12.58)				(19.25)	
spec3	57.98	1.07				6.5
	(11.64)	(13.37)				
spec4	64.77	-0.77			4.90	9.3
	(12.58)	(-7.37)			(18.56)	
spec4*	97.60	-0.72			4.82	10.7
	(15.34)	(-6.81)			(17.7)	
spec5*	97.93		0.67		3.28	10.9
	(15.34)		(5.87)		(13.11)	
spec6*	97.06	-0.75	0.70		4.40	11.1
	(15.43)	(-7.35)	(6.24)		(14.93)	
spec7*	96.59	-1.25		1.66	4.70	11.5
	(15.25)	(-11.59)		(8.36)	(17.24)	
spec8*	96.50	-1.20	0.35	1.44	4.51	11.6
	(15.38)	(-10.79)	(3.10)	(7.12)	(15.73)	

Table 3: Residual trading volume and firm characteristics (using market-adjusted volume)

We check whether the residual volume we calculate in Table 2 is independent of firm characteristics so that it can capture news characteristics well. Residual volume is calculated from market-adjusted trading volume by estimating regressions against many variables that are supposed to capture firm characteristics. For each specification, we report the relationship between residual volume and the mean of each variable used in regressions. High residual-volume group is the top 33% of the distribution in each quarter and low residual-volume group is the bottom 33%. |TDC| is the absolute value of the three-day sum of daily size-matched abnormal returns surrounding earnings announcements. P is share price and we take its log. Log(size) is the log of market capitalization at the end of the previous quarter. Institutional ownership data are from CDA/Spectrum and represent the percentage of firms' shares held by institutions. Analyst coverage is obtained from IBES consensus data. When a firm is not covered by CDA/Spectrum or IBES, we assign 0s to institutional ownership holding and analyst coverage. As in Table 2, we discard first size-quintile due to the very frequent appearance of 0 institutional ownership and 0 analyst coverage.

	Quintile based on TDC		residual trading volume	mkt adjusted volume	TDC	log(1+P)	log(size)	log(1+io)	log(1+an)
Spec 2	1st quintile	high residual trading volume	1.352	1.767	-7.9	2.26			
		low residual trading volume	-1.109	-0.433	-8.78	2.63			
	5th quintile	high residual trading volume	1.551	2.327	9.47	2.43			
		low residual trading volume	-1.193	-0.304	9.82	2.65			
Spec4	1st quintile	high residual trading volume	1.35	1.761	-7.88	2.26	11.39		
		low residual trading volume	-1.11	-0.43	-8.77	2.62	11.96		
	5th quintile	high residual trading volume	1.548	2.322	9.45	2.44	11.67		
		low residual trading volume	-1.198	-0.3	9.83	2.63	11.83		
Spec8	1st quintile	high residual trading volume	1.378	1.843	-7.57	2.45	11.84	2.62	0.82
		low residual trading volume	-1.147	-0.401	-8.4	2.74	12.25	2.99	1.08
	5th quintile	high residual trading volume	1.541	2.333	8.47	2.62	12.1	2.86	0.92
		low residual trading volume	-1.227	-0.266	9.04	2.74	12.11	3.1	1.07

Table 4: Drifts and residual trading volumes: Specification 2 in calculating residual trading volume

Drift60 is the sum of 60 daily size-matched abnormal returns outside of the earnings announcement window. For example, if a firm makes an earnings announcement at t, Drift60 is the sum of daily abnormal returns starting from t+2 and ending on t+63. Drift170 is similarly defined. SUE is the standardized unexpected earnings. It is the difference between current quarter's earnings and the corresponding quarter's earnings in the previous year normalized by the standard deviation of the difference. For each quarter, we choose firms that made announcements and divide firms depending on the magnitude of SUE. The first quintile consists of firms with the lowest SUE values (i.e., firms with negative news) and the fifth quintile consists of firms with the highest SUE values (i.e., firms with positive news). Residual trading volume is calculated from quarterly cross-sectional regressions. Here we use specification 2 in calculating residual trading volume. High residual-volume group is the top 33% of the distribution in each quarter and low residual-volume group is the bottom 33%. Each cell reports the size-matched abnormal return in %. P3 is the size-matched abnormal return of a high residual-volume cell and P1 is the size-matched abnormal return of a low residual trading volume cell. We also report the results for our second measure of surprise, TDC.

		SUE					TDC				
		1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Drift60	residual trading volume high	-1.43	-0.6	0.67	1.32	2.1	-0.5	-0.34	0.09	1	2.44
	residual trading volume low	-1.44	-1.29	-0.5	-0.26	0.33	-1.12	-1.31	-0.74	-0.27	0.11
	P3-P1	0.01	0.69	1.17	1.58	1.77	0.62	0.97	0.83	1.27	2.33
	(t-stat)	(0.03)	(2.16)	(3.98)	(5.19)	(5.67)	(1.72)	(3.39)	(2.93)	(4.51)	(6.59)
Drift170	residual trading volume high	-4.71	-2.24	-0.23	1.46	2.23	-2.2	-2.09	-1.07	0.08	3.09
	residual trading volume low	-3.17	-1.51	-0.4	-0.25	0.62	-1.79	-2.73	-1.69	-0.15	1.47
	P3-P1	-1.54	-0.73	0.17	1.71	1.61	-0.41	0.64	0.62	0.23	1.62
	(t-stat)	(-2.12)	(-1.04)	(0.28)	(2.68)	(2.47)	(-0.51)	(1.10)	(1.05)	(0.39)	(2.15)

Table 5: Drifts and residual trading volumes: Specification 8 in calculating residual trading volume

Drift60 is the sum of 60 daily size-matched abnormal returns outside of the earnings announcement window. For example, if a firm makes an earnings announcement at t, Drift60 is the sum of daily abnormal returns starting from t+2 and ending on t+63. Drift170 is similarly defined. SUE is the standardized unexpected earnings. It is the difference between current quarter's earning and the corresponding quarter's earnings in the previous year normalized by the standard deviation of the difference. For each quarter, we choose firms that made announcements and divide firms depending on the magnitude of SUE. The first quintile consists of firms with the lowest SUE values (i.e., firms with negative news) and the fifth quintile consists of firms with the highest SUE values (i.e., firms with positive news). Residual trading volume is calculated from quarterly cross-sectional regressions. Here we use specification 8 in calculating residual trading volume. High residual-volume is the top 33% of the distribution in each quarter and low residual-volume is the bottom 33%. Each cell reports the size-matched abnormal return in %. P3 is the size-matched abnormal return of high residual-volume cell and P1 is the size-matched abnormal return of low residual-volume cell. We also report the results for our second measure of surprise, TDC.

		SUE					TDC				
		1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Drift60	residual trading volume high	-1.02	-0.37	0.98	1.76	2.41	0.08	-0.006	0.23	1.3	2.82
	residual trading volume low	-1.13	-1.11	-0.32	-0.22	0.73	-1.07	-0.96	-0.6	-0.12	0.54
	P3-P1	0.11	0.74	1.3	1.98	1.68	1.15	0.954	0.83	1.42	2.28
	(t-stat)	(0.33)	(2.33)	(4.55)	(6.63)	(5.37)	(3.17)	(3.36)	(3.00)	(5.13)	(6.40)
Drift170	residual trading volume high	-3.44	-1.66	0.15	2.34	3.21	-1	-1.35	-0.54	0.74	4.11
	residual trading volume low	-2.62	-1.79	0.03	0.13	1.13	-1.21	-1.88	-1.46	-0.16	1.53
	P3-P1	-0.82	0.13	0.12	2.21	2.08	0.21	0.53	0.92	0.9	2.58
	(t-stat)	(-1.19)	(0.21)	(0.21)	(3.62)	(3.33)	(0.28)	(0.98)	(1.68)	(1.64)	(3.53)

Table 6. Comparison of Coefficient estimates for SUE by Residual-volume group

Panel A and B: TDC and 60-day drift are regressed on SUE and the product of SUE and residual volume calculated under specification 4 (control variables: magnitude of price change, firm size, and stock price), using the pooled sample. Panel A reports the regression results when the dependent variable is TDC, and B is when the dependent variable is 60-day drift. Panel C and D: for each quarter, we divide our observations into three residual-volume groups, where the residual volume is calculated under specification 4. In the respective residual-volume groups each quarter, TDC or 60-day drift is regressed on SUE. We compare the time-series means of the coefficient on SUE, and test the significance of the difference.

Panel A. Dependent variable: TDC

Intercept (*10^(-3))	SUE (*10^(-3))	SUE*Resvol (*10^(-3))
2.73	7.11	-0.0486
(11.38)	(39.70)	(-3.56)

Panel B. Dependent variable: Drift60

Intercept (*10^(-3))	SUE (*10^(-3))	SUE*Resvol (*10^(-3))
-3.09	6.43	0.147
(-5.46)	(15.21)	(4.58)

Panel C. Dependent variable: TDC

		Number of quarters	Mean (*10^(-3))	STD (*10^(-3))	t-stat for difference	p-value (%)
Residual volume	Low	34	8.71	3.17	2.65	1.01
	High	34	6.85	2.59		

Panel D. Dependent variable: 60-Day Drift

		Number of quarters	Mean (*10^(-3))	STD (*10^(-3))	t-stat for difference	p-value (%)
Residual volume	Low	34	3.34	5.81	-3.26	0.18
	High	34	8.34	6.79		

Table 7. Drift, residual trading volume, and institutional ownership

Drift170 is the sum of 60 daily size-matched abnormal returns outside of the earnings announcement window. For example, if a firm makes an earnings announcement at t, Drift170 is the sum of daily abnormal returns starting from t+2 and ending on t+173. io is institutional ownership holding. The first io-tertile consists of the bottom 30%. The second io-tertile consists of the 40% in the middle and the third io-tertile consists of the top 30%. . SUE is the standardized unexpected earnings. It is the difference between current quarter's earnings and the corresponding quarter's earnings in the previous year normalized by the standard deviation of the difference. We also report the results for our second measure of surprise, TDC. Each cell reports Drift 170 and t statistics in parentheses. Panel A reports drift patterns across each io-tertile. Panel B reports drift patterns across each io-tertile conditioning on residual trading volumes. Residual trading volume is calculated using market-adjusted trading volume and specification 4. High and low residual trading volumes are defined as in previous tables.

A. Drift170 and IO Tertile

		io					io		
		1st Tertile	2nd Tertile	3rd Tertile			1st Tertile	2nd Tertile	3rd Tertile
SUE	1st Quintile	-7.8	-2.8	-0.73	TDC	1st Quintile	-3	-1.08	-1.12
	5th Quintile	0.83	2.79	1.81		5th Quintile	3	2.23	2.87

B. Drift170, Residual Trading Volume and IO Tertile

			io		
			1st Tertile	2nd Tertile	3rd Tertile
SUE	1st Quintile	residual volume high	-9.84	-2.35	-1.13
		residual volume low	-6	-3.16	-0.35
		P3-P1	-3.84	0.81	-0.78
		(t-stat)	(-2.23)	(0.61)	(0.86)
	5th Quintile	residual volume high	1.92	3.76	2.5
		residual volume low	-0.77	1.64	0.9
		P3-P1	2.69	2.12	1.6
		(t-stat)	(1.61)	(1.63)	(2.05)

			io		
			1st Tertile	2nd Tertile	3rd Tertile
TDC	1st Quintile	residual volume high	-3.57	-1.94	-0.34
		residual volume low	-2.28	-0.36	-1.8
		P3-P1	-1.29	-1.58	1.46
		(t-stat)	(-0.76)	(-1.09)	(1.49)
	5th Quintile	residual volume high	2.27	3.97	4.71
		residual volume low	3.77	0.64	0.89
		P3-P1	-1.5	3.33	3.82
			(-0.89)	(2.34)	(4.11)

Table 8. Drift, residual trading volume, and size

Drift170 is the sum of 60 daily size-matched abnormal returns outside of the earnings announcement window. For example, if a firm makes an earnings announcement at t, Drift170 is the sum of daily abnormal returns starting from t+2 and ending on t+173. Size is market capitalization. The first size-tertile consists of the bottom 30%. The second size-tertile consists of the 40% in the middle and the third size-tertile consists of the top 30%. . SUE is the standardized unexpected earnings. It is the difference between current quarter's earnings and the corresponding quarter's earnings in the previous year normalized by the standard deviation of the difference. We also report the results for our second measure of surprise, TDC. Each cell reports Drift 170 and t statistics in parentheses. Panel A reports drift patterns across each size-tertile. Panel B reports drift patterns across each size-tertile conditioning on residual trading volume. Residual trading volume is calculated using market-adjusted trading volume and specification 4. High and low residual volumes are defined as in previous tables.

A. Drift170 and Size Tertile

		size					size		
		1st Tertile	2nd Tertile	3rd Tertile			1st Tertile	2nd Tertile	3rd Tertile
SUE	1st Quintile	-7.45	-4.33	-2.13	TDC	1st Quintile	-2.31	-1.76	-2.03
	5th Quintile	-0.84	2.47	1.75		5th Quintile	3.56	2.16	1.96

B. Drift170, Residual Trading Volume and Size Tertile

			size						size		
			1st Tertile	2nd Tertile	3rd Tertile				1st Tertile	2nd Tertile	3rd Tertile
SUE	1st Quintile	residual volume high	-10.9	-3.91	-2.41	TDC	1st Quintile	residual volume high	-3.98	-1.2	-1.53
		residual volume low	-4.41	-4.65	-1.86			residual volume low	0.46	-2.27	-2.41
		P3-P1	-6.49	0.74	-0.55			P3-P1	-4.44	1.07	0.88
		(t-stat)	(-2.92)	(0.54)	(-0.75)			(t-stat)	(-2.00)	(0.79)	(1.03)
	5th Quintile	residual volume high	0.31	3.63	2.66		5th Quintile	residual volume high	4.37	3.8	3.66
		residual volume low	-2.75	1	0.66			residual volume low	2.85	0.55	0.34
		P3-P1	3.06	2.63	2			P3-P1	1.52	3.25	3.32
		(t-stat)	(1.26)	(2.11)	(3.09)				(0.76)	(2.47)	(3.97)

Endnotes

[1] In fact, the models by Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) try to explain both underreaction and overreaction of investors in a way consistent with empirically observed price patterns. Jegadeesh and Titman (1993) report evidence on momentum, i.e., price continuation in the short to medium term. DeBondt and Thaler (1985) report return reversal at longer horizons. Our paper is about earnings momentum, thus we focus on the underreaction part of each model.

[2] There are several papers that test the implications of the BSV model and report evidence that supports the model's predictions (Kim and Rozhkov (1999), Wang (1999), Hvidkjaer (2000)).

[3] Thus, investors react to public news in a biased way (self-attribution bias) that will eventually generate overreaction.

[4] The clarity of information represents the degree to which investors agree on its content. Thus clear (or strong, salient) news will make the distinction between fully rational and underreacting investors less relevant since all the investors would behave as if they were fully rational investors. We use clarity and saliency of news interchangeably.

[5] When this paper was well under way, we became aware of a paper on a similar topic by Garfinkel and Sokobin (2000). They argue that large trading volume around an earnings announcement is caused by existence of diverse private opinions on public information, and drift could be observed as these private opinions become incorporated into prices. Thus, they argue that larger trading volume precedes larger drift. But, without the existence of underreacting investors, private opinions that do not become incorporated into the price on the announcement day should be orthogonal to the content of the public news. In this case, the direction of the drift caused by private opinions need not be in the same direction as the initial price reaction to the publicly observable part of the news.

[6]Bernard (1993) looks at the post-earnings announcement drift between 1974 and 1986. We also test whether our results are robust in earlier time periods. The results are not very different from the ones reported in this paper.

[7] The model in this paper closely follows the structure of Kandel and Pearson (1995).

[8] Our model does not consider trading costs explicitly. In the empirical part of the paper, we explicitly control for the differences in trading costs, since trading costs might affect the trading volume and the pattern of drift.

[9] We have also tried IBES analysts' mean forecast as the proxy for the expectation measure. The results are not affected by this change in the expectation measure.

[10] We form ten portfolios based on the year-end market capitalization. A size-matched abnormal return is the difference between an individual firm's return and a corresponding size decile portfolio's return.

[11] As is apparent from Panels A and B of Figure 1, a drift pattern is clearer when we use SUE as a surprise measure. The reason could be explained by endogeneity problems inherent in the TDC measure. While the SUE measure is exogenous to return changes, a TDC measure incorporates investors' reactions after the news is announced. Thus a low value of TDC could be due to little surprise after the news or could be due to extreme underreaction from investors.

[12] We windsorized our data at 1% and 99% of the distributions of the 60-day drift and market-adjusted volume to remove the effect of outliers. This does not make much difference in our results.

[13] We also run the market model over the 100 days prior to the announcement to calculate the market-adjusted volume. The results are robust to this specification change.

[14] In the empirical specification, one might be concerned about the possible negative correlation between the price change and residual trading volume. Even though this is a theoretical possibility, in our empirical scheme, it does not pose any significant threat to the unbiasedness of coefficient estimates since we are estimating cross-sectional regressions. Later in this section, we will check whether there is a systematic relationship between residual trading volume and absolute price changes. In fact, it turns out that residual trading volume obtained in cross-sectional regressions does not have a systematic relationship with price changes.

[15] We use heteroskedasticity-robust t-statistics.

[16] Results are similar when we use 170-day drift measure.