The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXI, NO. 1 • FEBRUARY 2016

The Calm before the Storm

FERHAT AKBAS*

ABSTRACT

I provide evidence that stocks experiencing unusually low trading volume over the week prior to earnings announcements have more unfavorable earnings surprises. This effect is more pronounced among stocks with higher short-selling constraints. These findings support the view that unusually low trading volume signals negative information, since, under short-selling constraints, informed agents with bad news stay by the sidelines. Changes in visibility or risk-based explanations are insufficient to explain the results. This evidence provides insights into why unusually low trading volume predicts price declines.

IN AN INFLUENTIAL STUDY, Gervais, Kaniel, and Mingelgrin (2001) document that unusually high (low) trading volume, measured over a day or a week, predicts higher (lower) future returns. This phenomenon is known as the *high volume return premium*. Their study spurred a flurry of research proposing explanations for this premium, such as changes in visibility or compensation for risk.[1] These explanations, however, mainly relate to the return premium due to unusually *high* volume—the relation between unusually *low* volume and future returns has received less attention, although it is equally important.[2] Our understanding of why unusually low volume predicts future returns therefore remains limited.

In this paper, I show that unusually low trading volume signals forthcoming negative information about changes in firm fundamentals, as captured

*Ferhat Akbas is from the School of Business, University of Kansas. I thank William Armstrong; George Bittlingmayer; Ekkehart Boehmer; Bilal Erturk; Egemen Genc; Chao Jiang; Ted Juhl; Ron Kaniel; Sami Keskek; Paul Koch; Felix Meschke; Ralitsa Petkova; Sorin Sorescu; Musa Subasi; Julie Wu; and seminar participants at the University of Kansas, the 2013 Southern Finance Association Meetings, and the 2013 Financial Management Association Meetings for helpful comments. I am particularly grateful to Kenneth Singleton (the Editor) and two anonymous referees for their insightful comments and suggestions. Part of the analysis in this paper was conducted while I was a PhD student at Texas A&M University. I have received no external financial support for this research and am aware of no conflicts of interest.

[1] See, for example, Garfinkel and Sokobin (2006), Barber and Odean (2008), Lerman, Livnat, and Mendenhall (2008), Gallmeyer, Hollifield, and Seppi (2009), Schneider (2009), Banerjee and Kremer (2010), and Kaniel, Ozoguz, and Starks (2012) for alternative explanations of the high volume return premium.

[2] Gervais, Kaniel, and Mingelgrin (2001) show that both high and low volume shocks significantly contribute to the high volume return premium. For example, among small firms where the return predictability is most observed, stocks with high (low) unusual volume outperform (underperform) stocks with normal volume by 50 (−50) basis points over a month.

DOI: 10.1111/jofi.12377

by earnings surprises.[3] I find that stocks with unusually low trading volume prior to earnings announcements experience significantly lower unexpected earnings compared to stocks with volume or unusually high volume. The results are stronger among stocks with binding short-selling constraints. In addition, I show that unusually low volume predicts abnormal returns around earnings announcements in a way that is consistent with the unexpected earnings prediction, with a strong relation between unexpected earnings predictability and return predictability. In contrast, while high unusual volume predicts higher returns, it does not predict positive changes in future fundamentals. These findings support the view that unusually low trading volume is a signal of bad news about firm fundamentals since, under short-selling constraints, informed agents with bad news (short sellers) stay by the sidelines. These findings further suggest that the underlying driver for the volume-prompted price movements is different for unusually high and low volume shocks.

The idea that, under short-selling constraints, unusually low trading activity is a signal of bad news is formalized in the seminal theoretical work of Diamond and Verrecchia (1987). According to Diamond and Verrecchia (1987), "Periods of the absence of trade are bad news because they indicate an increased chance of informed traders with bad news who are constrained from selling short" (p. 303). Their rationale is as follows.

Short sellers are informed traders whose trading activity signals negative information about firm fundamentals. If the stock market were frictionless, there would be no short-selling constraints and short sellers would freely trade on their information. In this case, trading activity in a stock and a stock's price would reflect current conditional expectations about the asset's value. However, in the presence of barriers to short selling, when unusually low trading volume is observed, it is not clear that short sellers choose not to trade. If we observe a sudden lack of trading in a stock under short-selling restrictions, the conditional expectation of the price will be upward biased since the negative information that short sellers possess is not incorporated into stock prices in a timely manner. Thus, unusually low trading volume may indicate a higher probability that, due to short-selling constraints, short sellers are forced to stay by the sidelines and hence the negative information they possess is not incorporated into prices. As a result, an unusual decrease in volume may signal bad news about the firm.

It should be noted that the Diamond and Verrecchia (1987) model assumes a pure rational expectations economy where investors learn from low trading volume instantaneously and incorporate its informational content into stock prices immediately. However, if price adjustment to low trading volume is not instantaneous and investors do not learn from trading volume immediately,

[3] By fundamental information, I mainly refer to information about changes in a firm's cash flow prospects.

then the model will arguably predict that unusually low trading volume contains negative information about future prices.[4]

Two explanations have been proposed to explain the return predictability due to unusual trading volume. The first argues that unusual volume predicts future returns due to a sudden change in a stock's visibility, as proposed by Miller (1977), Mayshar (1983), and Merton (1987).[5] However, in these models, the visibility of a stock changes mainly through unusually high volume: investor awareness of a stock might suddenly increase as a result of unusually high volume but is unlikely to suddenly decrease following unusually low volume. Because of this asymmetry, the relation between unusually low volume and future returns would be hard to explain with the visibility hypothesis.[6]

The second explanation argues that the high-volume return premium is compensation for risk. For example, Banerjee and Kremer (2010) argue that unusually high volume reflects a high level of disagreement about the future, which leads to increased uncertainty and risk today.[7] Alternatively, Schneider (2009) suggests high trading volume implies low information quality and thus higher uncertainty. Gallmeyer, Hollifield, and Seppi (2009) further propose that large volume signals an unusual degree of uncertainty about investor demand for a stock. In each of these models, the focus is on understanding why unusually high volume predicts future returns and the return-predictive power associated with unusually low volume receives little attention.

In this paper, I examine the nature of the information that is signaled by unusually low volume. My primary contribution is to present evidence that unusually low volume signals unfavorable changes in firm fundamentals. The fundamental information channel provides an important and alternative explanation for the association between low volume shocks and future returns. To the best of my knowledge, this is the first paper to empirically document the relation between unusually low volume and firm fundamentals.[8]

[4] Relaxing the pure rational expectations assumption is reasonable, since ample evidence suggests that price adjustments to information are far from instantaneous. For example, the literature on short selling (see Boehmer, Jones, and Zhang (2008)), price momentum (Hong, Lim, and Stein (2000)), insider trading, (Seyhun (1986, 1998), Lakonishok and Lee (2001)), and unusual volume shocks (Gervais, Kaniel, and Mingelgrin (2001)) suggest that price adjustments to information are far from instantaneous.

[5] Miller (1977) focuses on overvaluation of prices due to excess demand under short-sale restrictions, and Merton (1987) focus on the reduction in the estimation risk faced by traders due to an increase in a stock's investor base after experiencing excess buy-side demand. Barber and Odean (2008) claim that the high volume premium can be explained by Miller (1977). Kaniel, Ozoguz, and Starks (2012) provide evidence in favor of Merton's (1987) explanation of the high-volume return premium.

[6] Chen, Noronha, and Signal (2004) make a similar argument regarding the asymmetric price reaction after additions to and deletions from the S&P 500 index. They argue that investor recognition will increase after listing on the index, but will not decrease suddenly after delisting.

[7] Varian (1985) also argues that high volume levels capture disagreement among investors from a risk perspective.

[8] Gervais, Kaniel, and Mingelgrin (2001, p. 912) briefly discuss the implications of Diamond and Verrecchia (1987) but do not discuss these implications in detail or present any formal test. Reed

To check the plausibility of the information argument, I conduct two tests. First, if unusually low volume signals the information that short sellers possess but cannot trade, then the extent of short sellers' trading activity should reduce the information content of unusually low volume. I show that monthly short interest negatively predicts earnings surprises, and the information content of unusually low volume is significantly lower among stocks with higher short interest. Moreover, when short sellers use put options to trade on their negative information, unusual put option volume predicts earnings surprises and significantly attenuates the negative information content of unusually low volume. In contrast, unusual call option volume does not affect the information content of unusually low volume. Second, using content analysis of firm-specific public news around earnings announcement dates, I show that unusually low trading volume predicts negative sentiment in forthcoming news about stocks. In contrast, unusually high volume does not predict the sentiment in public news. These results therefore provide additional evidence that unusually low trading activity signals negative information.

Earnings announcements provide a natural environment to test the information content of unusually low trading volume.[9] Earnings announcements are important exogenously scheduled information disclosure events that occur frequently at known intervals. An earnings surprise on an announcement date conveys new information to the market about the company's expected cash flows and thus can be used to determine whether any signal prior to the announcement contains substantive information about firm fundamentals. Importantly, the information revealed at the announcement can be measured using not only stock returns, but also analyst forecasts and accounting-based measures of earnings, which enables us to distinguish the information argument from the visibility and risk arguments.

Several prior papers also examine trading volume around earnings announcements.[10] For example, Garfinkel and Sokobin (2006) and Lerman, Livnat, and Mendenhall (2008) study the relation between unexpected volume on the announcement date and postearnings announcement drift. In line with the visibility argument, Frazzini and Lamont (2006) show that stocks with unusually high volume over the month of the earnings announcement have a higher return premium over the same month. Chae (2005) documents a decrease in abnormal trading volume of more than 15% prior to earnings announcements, and concludes that discretionary liquidity traders are less willing to trade under information asymmetry. Using the average level of trading volume as a measure of divergence of opinion, Berkman et al. (2009) find that stocks with

(2007) discusses the implications of short selling on information diffusion but does not link this to the relation between future returns and unusually low volume.

[9] Several studies use earnings announcement surprises to detect the information content of trading by analyzing the trades of different market participants such as institutions (Campbell, Ramadorai, and Schwartz (2009)), mutual fund managers (Baker et al. (2010)), or individuals (Kaniel et al. (2012)) prior to earnings announcements.

[10] See Bamber, Barron, and Stevens (2011) for an extensive literature review on trading volume around earnings announcements.

higher volume earn significantly lower returns around earnings announcements.[11] This paper differs from these studies by focusing on the information content of unusually *low* volume before earnings announcements.

The current study is also related to the literature on the absence of insider trading and future returns. Marin and Olivier (2008) show that, following a period of intense insider trading, lower insider sales is bad news. Gao and Ma (2012) further show that, when insiders do not trade for a long time, this insider "silence" signals extreme news about earnings. This paper complements these studies by showing that, in addition to the silence of certain informed traders, such as insiders, the silence of (i.e., lack of trading by) general market participants also contains negative value-relevant information. Hence, silence also represents an informative market phenomenon that has broad implications for the stock market.

The rest of the paper is organized as follows. Section I discusses key variables and sample selection. Section II documents the relation between unusually low volume and fundamental information. The effect of short-sale restrictions on this relation is presented in Section III. Section IV presents results on the relation between earnings announcement returns and unusually low volume. Section V provides additional evidence using short sellers' trades and public news around earnings announcements. Section VI presents robustness checks. Section VII concludes.

I. Variables and Sample Selection

A. Unusual Volume

Following Gervais, Kaniel, and Mingelgrin (2001), I measure unusual volume by comparing a stock's average daily turnover over the week (*event period*, totaling five days, [−6,−2]) prior to a Compustat earnings announcement date (*day* 0) and the stock's previous 10 weeks of turnover (*reference period*, totaling 50 days, [−61,−12]) prior to the Compustat earnings announcement date, where daily turnover is defined as daily total shares traded divided by the number of shares outstanding. In particular, a stock is classified as a low (high) volume stock if its event period volume is in the bottom (top) 20% of its 10-week *reference period* volume.[12] As in Gervais, Kaniel, and Mingelgrin (2001), this method classifies a stock as a low, normal, or high volume stock by comparing its event period volume to its own trading volume history, and thereby captures the *absolute* change in its trading volume rather than a *relative* change.

[11] While the high level of trading volume is negatively related to future returns (Brennan and Subrahmanyam (1996), Chordia, Subrahmanyam, and Anshuman (2001)), it is the unusual level of trading volume that is positively correlated with future returns. Also, Berkman et al.'s (2009) explanation relies on high trading volume, and does not explain why low levels of volume should have any information about earnings surprises.

[12] I chose 20% to ensure that there are enough stocks in both the low and high unusual volume groups, particularly for the analysis in which I use analyst forecast surprise measures.

I next construct dummy variables for unusually low volume, *D_LOW*, and unusually high volume, *D_HIGH*, that indicate whether a stock has unusually low or high volume in a given quarter. In particular, *D_LOW* equals one if a stock is classified as a low volume stock in quarter q and zero otherwise and *D_HIGH* equals one if a stock is classified as a high volume stock in quarter q and zero otherwise. I require that sample stocks have no missing daily trading volume data over the entire reference and event periods. The use of dummies instead of a continuous measure of unusual volume allows me to separately examine the effects of unusually high versus low volume shocks. The results are similar if I instead use the ratio of event period volume to reference period volume as a continuous measure of unusual volume.

B. Earnings Surprise Measures

I capture earnings surprises using three measures. The first two measures are based on actual earnings: standardized unexpected earnings using historical accounting information (*SUE*) and standardized unexpected earnings using analyst forecasts (*SUEAF*). To construct *SUE*, I first calculate unexpected earnings using a seasonal random walk model, $UE_{iq} = (X_{iq} - X_{iq\text{-}4})$, where X_{iq} and $X_{iq\text{-}4}$ are firm i's earnings per share (EPS) before extraordinary items in quarters q and $q-4$, respectively.[13] I next divide unexpected earnings (UE_{iq}) by $q-4$ quarter-end stock prices, P_{iq-4}, to obtain standardized unexpected earnings, *SUE*. The variables X_{iq-4} and P_{iq-4} are adjusted for any stock splits and stock dividends during the period, $\{q-4, q\}$. The advantage of this measure (as opposed to other measures requiring a longer time series of earnings) is that it can be estimated for almost every firm-quarter in the Compustat database, resulting in a larger sample. To eliminate outliers, each quarter I exclude the top and bottom 1% of observations from the sample. I also require that sample stocks have valid earnings in the quarters between q and $q-4$.

To construct standardized unexpected earnings using analysts' forecasts, *SUEAF*, I first take the difference between actual EPS reported in I/B/E/S and the median of the most recent analyst forecasts over the 90 days prior to the earnings announcement. I then scale this difference by $q-4$ quarter-end stock prices, P_{iq-4}. Similar to *SUE*, I exclude the top and bottom 1% of observations from the sample to eliminate the effect of outliers. One disadvantage of using analyst forecasts to capture the earnings surprise is that the resulting measure only reflects the surprise relative to the opinions of analysts, that is, it ignores the information provided by other well-informed market participants. Moreover, since not all stocks are followed by analysts, I lose more than half of the sample observations and am forced to rely on a sample that largely comprises bigger firms.

[13] Foster, Olsen, and Shevlin (1984) show that the seasonal random walk model's forecast errors perform as well as more advanced time-series techniques to capture the earnings surprise. Among others, Livnat and Mendenhall (2006), Johnson and So (2012), and Garfinkel and Sokobin (2006) also use the difference across quarters q and $q-4$.

Overall, the use of two earnings-based surprise measures offers a robustness check on the validity of my findings. In addition, the value-relevant information content of *SUE* and *SUEAF* helps me demonstrate that the underlying driver for the volume-prompted price movements is different for unusually high and low volume shocks as the latter are associated with negative fundamental information.

The third earnings surprise measure is based on the abnormal stock return around an earnings announcement. In particular, a stock's cumulative abnormal return (*CAR*) is defined as the difference between the firm's compounded stock return and value-weighted market return (in percent) over the three-day window $[-1, +1]$ around the earnings announcement date (day 0). Data on earnings announcement dates come from Compustat.[14] While in general stock prices reflect changes in either expected cash flows or expected returns (Campbell (1991)), abnormal returns around earnings announcements are mainly driven by firm-specific idiosyncratic cash flow news. Thus, similar to *SUAEF* and *SUE*, *CAR* also captures the importance of the fundamental information revealed by the announcement (Kothari, Lewellen, and Warner (2006)). Moreover, the return-based measure is a forward-looking measure that reveals the market's expectation regarding the firm's future cash flow prospects of the company. By reflecting the overall opinions of all market participants at the time of the announcement, *CAR* helps quantify the economic value of the surprise.

One important drawback of the abnormal return measure is that other factors unrelated to information about the firm's cash flows or fundamentals, such as shocks related to liquidity, risk, or visibility, may affect the magnitude of the surprise. In a subsample based on the availability of all three measures, the time-series average of the cross-sectional correlation between *CAR* and *SUE* is 0.13, between *SUEAF* and *SUE* is 0.37, and between *CAR* and *SUEAF* is 0.27.[15] The moderate positive correlation between *CAR* and *SUE* (*SUAEF*) confirms that abnormal returns (*CAR*) around announcements capture not only value-relevant information at the announcement but also other factors.

C. Control Variables

I include several control variables in the analysis. First, I include *SIZE*, the market value of equity calculated as the previous quarter-end number of shares outstanding times the share price, and *BM*, the ratio of the previous quarter-end book value to market value of equity,[16] where I use logged values of *BM* and *SIZE* to mitigate the effect of considerable skewness in these

[14] Among others, Lerman, Livnat, and Mendenhall (2008) and Berkman et al. (2009) use the same window to measure the CAR. This window ensures that my results are not driven by information leakages just before the announcement or by potential misalignment of data around announcement date.

[15] Livnat and Mendenhall (2006) find similar correlations for these three surprise measures.

[16] Book value is calculated as in Fama and French (2002). Only firms with positive book values are included.

variables. Next, I include *RET_50*, the 50-day reference period return computed over the [−61,−12] window prior to the earnings announcement date, and *RET_5*, the five-day event period return computed over the [−6,−2] window prior to the earnings announcement date. I also include *IVOL*, the standard deviation of daily returns calculated over days [−11,−2] prior to the earnings announcement, to capture the influence of return volatility, since many studies document that trading volume has a high contemporaneous correlation with price volatility (see Wang (1994)). I next include *IO*, the firm's institutional ownership, defined as the previous quarter-end sum of the holdings of all institutions for each stock (obtained monthly from 13F filings through Thomson Financial since 1980) divided by the number of shares outstanding (obtained from CRSP). I assume that, if a stock has available return data but no reported institutional holdings, it has zero institutional ownership.[17] Since I use one-quarter-lagged institutional ownership to measure the institutional ownership of the current quarter, the sample starts from the second quarter of 1980. Institutional ownership is used to capture the effect of short-sale restrictions. To ensure that the results not merely capture an average volume effect as documented in Berkman et al. (2009), I also control for the average turnover (*TURN_50*) over the reference period, [−61,−12]. Finally, since previous earnings surprises are known to be associated with future earnings surprises (Chan, and Lakonishok (1996)), I control for the earnings surprises in the preceding quarter, *LAG_SURPRISE*.

D. Sample Selection and Summary Statistics

In this section, I present summary statistics for each data sample used in my analysis. Each quarter I calculate cross-sectional summary statistics for the firm characteristics. I then compute the time-series averages of these quarterly summary statistics. All data samples consist of NYSE, NASDAQ, and Amex common stocks. I exclude stocks with a previous quarter-end price of less than two dollars to ensure that the results are not driven by extremely illiquid stocks. Further, I include only stocks with at least 12 months of past return data from CRSP, and sufficient data from Compustat to compute the relevant accounting ratios for December of the previous year.

In Panels A and B of Table I, I present summary statistics for the sample based on the unexpected earnings samples. In Panel A, I present the statistics for the sample based on the availability of the *SUE* measure. The sample covers

[17] Under the 1978 amendment to the Securities and Exchange Act of 1934, if institutional investors hold equity positions (long) greater than 10,000 shares or $200,000 in market value, they are required to file quarterly 13F reports with the SEC at the end of each quarter. Hence, missing values of institutional ownership simply suggest that institutions do not hold the stock or do so in very small amounts. It is standard procedure to assume that missing data on institutional ownership reflect no institutional ownership. See Nagel (2005), Boehme, Danielsen, and Sorescu (2006), Boehmer and Kelley (2009), and Berkman et al. (2009).

Table I

Summary Statistics

The table presents time-series averages of quarterly summary statistics of various firm characteristics for *CAR*, *SUE*, and *SUEAF* earnings surprise measure samples. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. Panel A presents summary statistics for *SUE* sample. *SUE* is standardized unexpected earnings defined as the difference in EPS before extraordinary items in quarters q and $q-4$ divided by quarter $q-4$ end price (in %). Panel B presents summary statistics for the *SUEAF*. *SUEAF* is the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by the $q-4$ quarter-end price (in %). Panel C presents summary statistics for the *CAR* sample. *CAR* is defined as the compounded return over the [−1, +1] window around the earnings announcement in excess of the compounded value-weighted market return (in %). *SIZE* is market value of equity (in billions), *IO* is the percentage of shares owned by institutions as reported in 13F filings, *RET_50* is the 50-day reference period return (in percent) computed over the [−61,−12] window prior to the earnings announcement date, *RET_5* is the return (in percent) computed over the [−6,−2] window prior to earnings announcement date, *IVOL* is standard deviation of daily returns calculated over the 10 days [−11,−2] prior to the earnings announcement date, *BM* is the ratio of the book value to the market value of equity, *TURN_50* is average turnover over the period [−61,−12], and *Lag_CAR*, *LAG_SUE*, and *LAG_SUEAF* are surprise measures in the preceding quarter.

Panel A: *SUE* Sample

Sample Period: 1980:Q2–2011:Q4 (127 Quarters)
Average # of Stocks: 2,023
# of Observations: 256,864

	Mean	Median	STD	P_10	P_25	P_75	P_90
SUE	0.30	0.15	3.72	−0.65	0.88	2.89	−2.38
SIZE	2.52	0.31	10.28	0.09	1.29	4.67	0.04
BM	0.76	0.62	0.73	0.36	0.97	1.41	0.21
RET_50	3.54	1.97	19.61	−7.42	12.13	24.64	−16.91
RET_5	0.43	0.02	6.69	−2.99	3.32	7.63	−6.52
IO	0.44	0.45	0.23	0.26	0.63	0.74	0.12
TURN _50	0.05	0.04	0.06	0.02	0.06	0.11	0.01
Lag_SUE	0.50	0.16	8.20	−0.63	0.91	3.07	−2.36
IVOL	0.03	0.02	0.02	0.02	0.03	0.05	0.01

Panel B: *SUEAF* Sample

Sample Period: 1987:Q1–2011:Q4 (100 Quarters)
Average # of Stocks: 1,115
# of Observations: 111,510

	Mean	Median	STD	P_10	P_25	P_75	P_90
SUE	−0.02	0.03	0.66	−0.52	−0.12	0.18	0.48
SIZE	5.37	1.10	16.28	0.16	0.36	3.61	11.15
BM	0.61	0.48	0.57	0.16	0.28	0.78	1.14
RET_50	2.75	1.78	18.75	−17.84	−7.76	11.78	23.55
RET_5	0.35	0.04	6.56	−6.62	−3.11	3.41	7.57
IO	0.60	0.63	0.19	0.33	0.48	0.75	0.83
TURN _50	0.08	0.06	0.08	0.03	0.04	0.09	0.16
Lag_SUEAF	−0.02	0.03	1.22	−0.51	−0.12	0.18	0.50
IVOL	0.03	0.02	0.02	0.01	0.02	0.03	0.05

(*Continued*)

Table I—*Continued*

Panel C: *CAR* Sample

Sample Period: 1980:Q2–2011:Q4 (100 Quarters)
Average # of Stocks: 2,886
# of Observations: 366,454

	Mean	Median	STD	P_10	P_25	P_75	P_90
SUE	0.13	−0.10	8.26	−8.30	−3.69	3.63	8.65
SIZE	2.05	0.23	9.08	0.03	0.07	0.95	3.58
BM	0.77	0.59	0.84	0.18	0.33	0.97	1.45
RET_50	3.43	1.58	21.8	−18.9	−8.56	12.6	26.4
RET_5	0.42	0.01	7.25	−7.02	−3.21	3.46	8.13
IO	0.40	0.40	0.24	0.08	0.21	0.59	0.72
TURN _50	0.05	0.04	0.07	0.01	0.02	0.07	0.11
Lag_CAR	0.33	−0.03	8.45	−8.12	−3.60	3.77	8.91
IVOL	0.03	0.02	0.02	0.01	0.02	0.04	0.05

the period from the second quarter of 1980 to the end of 2011 (for a total of 127 quarters). There are 256,864 firm-quarter observations in this sample, for an average of 2,023 stocks each quarter. The mean (median) *SUE* is 0.3 (0.15), indicating that the average difference in EPS in quarter q and $q-4$ is 0.3% of the $q-4$ quarter-end price per share. In Panel B of Table I, I present the same characteristics for the *SUEAF* sample, which extends from the first quarter of 1987 to the end of 2011 (for a total of 100 quarters). This sample contains 111,510 firm-quarter observations, for an average of 1,177 stocks per quarter. The mean (median) *SUEAF* is −0.02 (0.03), indicating that the average difference in *EPS* across quarters q and $q-4$ is 0.02% of the $q-4$ quarter-end price per share.

In Panel C of Table I, I present summary statistics for the return-based earnings surprise measure, *CAR*. The sample period is from the second quarter of 1980 to the end of 2011 (for a total of 127 quarters). There are 366,454 firm-quarter observations in this sample, for an average of 2,886 stocks each quarter. The mean (median) CAR is 13 (−10) basis points over the three days around the earnings announcement. The significant CAR of 13 basis points suggests that, on average, earnings surprises are positive.

When I compare the samples across the three panels in Table I, the total number of observations is largest for the *CAR* sample, indeed, it is almost three times larger than that for the *SUEAF* sample. The reduction in sample size for the *SUEAF* sample is due to the fact that firms must be followed by at least one analyst to be included in the sample, and many smaller firms are not followed by an analyst. As a result of this sample selection, the mean market capitalization, *SIZE*, is lowest for the *CAR* sample (2.05 billion dollars), increasing to 2.52 billion dollars and 5.37 billion dollars for the *SUE* and *SUEAF* samples, respectively. Similarly, the average *IO* is lowest for the *CAR* sample (0.39), increasing to 0.43 and 0.59 for the *SUE* and *SUEAF* samples, respectively.

II. Unusually Low Volume and Fundamental Information

In this section, I use earnings-based surprise measures *SUE* and *SUAEF* to examine the information content of unusually low trading volume about changes in firm fundamentals. I begin the analysis using these two measures of earnings surprises because they capture the information embodied in the earnings surprise at the announcement using either historical accounting data or analyst forecasts. Visibility or risk-related shocks prior to earnings announcements cannot affect the information content of these earnings surprises. Therefore, any relation between unusually low volume and these earnings surprise measures would provide strong support for the information content of unusually low volume shocks about firm fundamentals and would distinguish the information story from visibility or risk-based arguments that explain the association between high volume shocks and future returns.

A. Portfolio Analysis

I first analyze the relation between unusually low volume shocks and earnings surprises using portfolio sorts. Each quarter I classify stocks into quintiles based on unusual volume and I calculate the cross-sectional mean earnings surprise for each unusual volume quintile. I then compute the time-series (weighted) averages of these cross-sectional means across all quarters.[18] The results are presented in Figure 1, Panels A and B for *SUE* and *SUEAF*, respectively.

In Figure 1, Panel A, I present the average *SUE* for the unusual volume quintiles. The relation between *SUE* and unusual volume seems to follow a linear pattern whereby the stocks with low unusual volume (UV1) tend to experience a relatively lower earnings surprise compared to stocks with normal or high unusual volume. The difference between the mean *SUE* for the lowest (UV1) and highest (UV5) unusual volume groups is 0.163, significant at the 1% level. When I examine the low and normal volume groups (UV1 and UV3), the difference in mean *SUE* is 0.115, significant at the 1% level. Finally, the analogous difference between the middle and high volume groups (UV3 and UV5) is 0.048, not significant at any acceptable level.

In Figure 1, Panel B, I present the average *SUEAF* for unusual volume shocks. When I examine the pattern in *SUEAF* for the top four quintiles by unusual volume (skipping the UV1 group), the pattern of the relation between *SUEAF* and unusual volume is flat, with the mean *SUEAF* close to zero. However, the mean *SUEAF* for quartile 1 is negative at −0.024. As a result, the difference between the mean *SUEAF* across UV1 and UV5 is −0.019, and is significant at the 1% level. Similarly, when I examine the difference in average *SUEAF* between the low and normal volume groups (UV1 and UV3), the difference is −0.021, significant at the 1% level. Finally, the difference between the

[18] Weights are based on the number of observations in each quarterly group according to unusual volume.

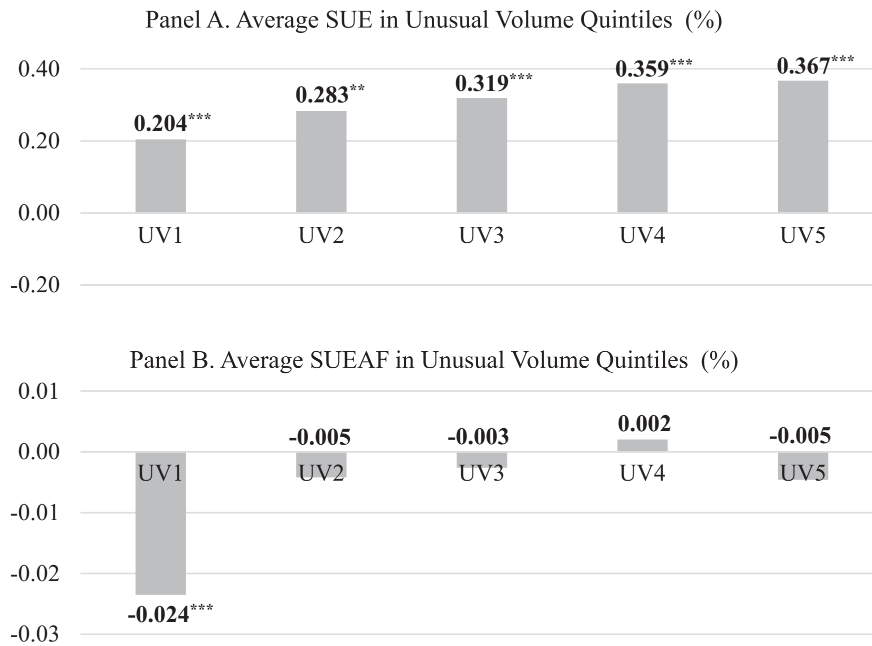

Figure 1. Average unexpected earnings, *SUE* and *SUEAF*, by unusual volume quintiles. The figures present time-series averages of quarterly mean values of unexpected earnings, *SUE* and *SUEAF*, within unusual volume quintiles. The weights are based on the number of observations in each unusual volume quintiles each quarter. Every quarter stocks are classified into unusual volume quintiles (UV1–UV5) based on their event period volume's rank, defined as average turnover over the $[-6,-2]$ window prior to the earnings announcement, compared to their own past 10-week volume measured over the reference period $[-61,-12]$ window prior to the earnings announcement date. All samples contain common stocks listed on the NYSE, AMEX, and NASDAQ. *SUE* is standardized unexpected earnings defined as the difference in EPS before extraordinary items between quarters q and $q-4$ divided by the $q-4$ quarter-end price. In the *SUE* sample, there are 256,864 stock-quarter observations over the sample period 1980:Q2 to 2011:Q4 (127 quarters). *SUEAF* is the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by the $q-4$ quarter-end price. In the *SUEAF* sample, there are 111,510 stock-quarter observations over the sample period 1987:Q1 to 2011:Q4 (100 quarters). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

middle (UV3) and high (UV5) unusual volume groups is 0.02, not statistically significant.

The trends depicted in the bar charts in Figure 1, Panels A and B, suggest that unusually low volume conveys negative information about unexpected earnings. However, the magnitude of each bar likely provides a biased estimate of the actual economic information being conveyed. For example, in Figure 1, Panel A, the historical growth in EPS might explain why all bars are positive, in which case these bars likely overestimate the actual information being conveyed by the unusual volume. Moreover, it is well established that analysts' forecasts are generally optimistic.[19] Such optimism would imply that analysts' earnings forecasts are on average higher than actual EPS due to analysts' optimism, which would explain the negative average *SUEAF* in Panel B of Table I and the negative bars in Figure 1, Panel B. Unless these different biases systematically affect one unusual volume group more than others, comparing relative surprises between low and high unusual volume groups should provide a fairly good picture of the effect of unusual volume on surprises.

Overall, the results in Figure 1, Panels A and B, suggest that stocks with low volume shocks prior to earnings announcements experience significantly lower earnings surprises when compared to stocks without any volume shocks (UV3) or to stocks with high volume shocks (UV5). Finally, although the pattern seems to be linear for *SUE*, the nonlinear pattern for *SUAEF* is clearly due to stocks with low volume shocks (UV1).

B. Regression Analysis

In this section, I perform a cross-sectional regression analysis that controls for various stock characteristics that may affect the relation between volume shocks and a stock's earnings surprise. I estimate quarterly weighted Fama and MacBeth (1973) regressions in which the dependent variable is the earnings surprise. To do so, I first run the following cross-sectional regression every quarter:

$$Surprise_{i,q} = \alpha_q + \beta_{1,q} \times D\_LOW_{i,q} + \beta_{2,q} \times D\_HIGH_{i,q} + \beta_{x,q} \times Controls_{i,q} + \varepsilon_{i,q}, \quad (1)$$

where i refers to the stock, q refers to the calendar quarter, and $Surprise_{i,q}$ is the earnings surprise for firm i in quarter q, measured using *SUE* or *SUEAF*. I then average (weighted) the cross-sectional coefficients across all quarters, where the weights correspond to the number of observations in each quarterly cross-sectional regression. Using a quarterly frequency is a reasonable choice, since most firms make quarterly announcements. Several other papers in the literature use calendar quarters to perform Fama and MacBeth (1973) regressions to analyze earnings surprises (e.g., Garfinkel and Sokobin (2006), Berkman et al. (2009), and Johnson and So (2012)). Note that, although the specific announcement dates differ across firms within a quarter, which may potentially affect the correlation between firm-specific errors in the cross-sectional regressions, it does not affect our inferences as correlation between firms is allowed in Fama-MacBeth regressions.

In all regressions, the main variable of interest is the low volume shock dummy, *D_LOW*. The coefficient on this variable captures the difference in the earnings surprise across stocks with unusually low volume versus those with normal volume prior to an earnings announcement, after controlling for the effect of high volume shocks, *D_HIGH*, as well as control variables that might affect the announcement outcome. The results are presented in Table II.

[19] See Lin and McNichols (1998), Hong and Kubik (2003), O'Brien, McNichols, and Lin (2005), and Barber, Lehavy, and Trueman (2007), among others for evidence on analysts' optimism.

Table II

Unusually Low Volume as Predictor of Earnings Surprise

The table presents results of quarterly weighted Fama and MacBeth (1973) regressions using *SUE* and *SUEAF* as the dependent variables. The weights correspond to the number of observations used in each quarterly cross-sectional regression. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. S*UE* is standardized unexpected earnings defined as the difference in EPS before extraordinary items between quarters q and $q-4$ divided by the $q-4$ quarter-end price. *SUEAF* is the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by quarter $q-4$ end price. A stock is classified as a low (high) extreme volume stock if its event period volume, defined as average turnover over the [−6,−2] window prior to earnings announcement, is among the bottom (top) 20% of the 10-week reference period volume over the [−61,−12] window prior to the earnings announcement date. Low unusual volume dummy, *D_LOW*, equals one if a stock is classified as a low extreme volume stock and zero otherwise. Similarly high unusual volume dummy, *D_HIGH*, equals one if a stock is classified as a high extreme volume stock and zero otherwise. The remaining control variables are defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Coefficient estimates are multiplied by 100. Newey and West (1987) t-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	SUE (1)	*SUEAF* (2)
D_LOW	−0.065***	−0.019***
	−2.80	−3.13
D_HIGH	0.001	0.002
	0.02	0.33
SIZE	−0.053**	0.010***
	−2.40	3.37
BK	−0.241***	−0.048***
	−3.76	−4.11
RET_50	1.987***	0.454***
	11.08	7.07
RET_5	2.655***	0.673***
	9.59	5.29
IO	−0.174	0.089***
	−1.14	3.93
IVOL	4.647	−1.6***
	0.89	−2.97
LAG_SURPRISE	9.063***	10.154***
	13.85	15.53
TURN_50	0.035	−0.007
	0.53	−1.05
Constant	0.709***	−0.192***
	2.58	−3.71
Adj. R^2	7.2%	7.6%
# of firm-quarter obs.	256,864	111,510
Sample period	1980:Q2−2011:Q4	1987:Q1−2011:Q4
	(127 quarters)	(100 quarters)

The results show that the coefficients on the unusually low volume dummy (*D_LOW*) are negative and highly significant at the 1% level for both *SUE* and *SUAEF*. In other words, stocks with low unusual volume prior to earnings announcements tend to have significantly lower earnings surprises, when compared to normal or high volume stocks, using both measures of earnings surprises. These results cannot be explained by differences in firm size, book-to-market, institutional ownership, average trading volume, past stock price performance, price performance immediately before the earnings surprise, stock return volatility, or persistence in the earnings surprise.

Turning to the coefficients on the unusually high volume dummy (*D_HIGH*), I note that Diamond and Verrecchia's (1987) model does not predict any relation between *D_HIGH* and future earnings surprises. In my empirical tests in Table II, I find no significant relation between *D_HIGH* and the *SUE* or *SUEAF* measures of earning surprises. This finding suggests that high volume shocks do not signal positive information about firm fundamentals.

Overall, the results in Table II provide strong support for the view of this paper that unusually low volume contains unfavorable information about firm fundamentals as captured by earnings surprise measures based on actual earnings. Further, since visibility or risk-based arguments do not predict any relation between unusual volume and fundamental information, the results also refute the alternative arguments that visibility or risk-based explanations can explain the findings. The insignificant coefficients on *D_HIGH* are also important as they demonstrate that the results are not symmetric for low and high volume shocks, and hence that the information content of low and high volume shocks is different.

III. Unusually Low Volume, Fundamental Information, and Short-Sale Restrictions

According to Diamond and Verrecchia (1987), low volume shocks signal bad news when short sellers are forced to stay by the sidelines due to short-selling constraints. The information content of unusually low volume should therefore be higher among stocks with more binding short-selling constraints. In this section, I test this argument using two different proxies for short-selling restrictions, namely, institutional ownership and the presence of exchange-traded options.[20]

A. Institutional Ownership as a Proxy for Short-Sale Restrictions

Following prior literature,[21] the first proxy for short-selling restrictions is institutional ownership (*IO*). Institutions are a major source of lending. If a stock's shares are predominantly held by nonlending investors, then short-selling constraints are more likely to be binding. Accordingly, low institutional ownership should be associated with higher short-selling constraints, and in

[20] A finer and more direct measure of short-sale constraints would be the average loan fee for institutional loans involved in short selling. See D'Avolio (2002), Geczy, Musto, and Reed (2002), and Johnson and So (2012). However, data on loan fees are available only for a very short time period, and thus are not very useful for the quarterly analysis of this paper.

[21] See, for example, D'Avolio (2002), Chen, Hong, and Stein (2002), Asquith, Pathak, and Ritter (2005), Nagel (2005), Berkman et al. (2009), and Akbas et al. (2014).

turn the effect of low volume shocks should be higher among stocks with low institutional ownership.

To test this conjecture, I provide regression estimates using two different specifications. In the first specification, I include an interaction term between *IO* and the unusually low volume dummy, *D_LOW*. However, since larger firms tend to have higher institutional ownership, one might argue that any effect of institutional ownership on the relation between *D_LOW* and earnings surprises might simply be driven by firm size rather than institutional ownership. To the extent that this is the case, since larger firms are more liquid and informationally efficient, the results could conceivably be driven by liquidity or information uncertainty effects rather than short-selling restrictions. To control for this effect, in the second specification I add an interaction between *SIZE* and *D_LOW* in addition to the interaction between *IO* and *D_LOW*. If short-selling restrictions amplify the relation between low volume shocks and earnings surprises (*SUE* and *SUEAF*), then I should find a positive coefficient on the interaction term between *IO* and *D_LOW* in both specifications.

Panel A of Table III reports Fama and MacBeth (1973) regression coefficients. When the surprise is measured using *SUE*, in the first specification the coefficient on *D_LOW* is −0.257, significant at the 1% level with a *t*-value of −3.49. The coefficient on *D_LOW* reflects the effect of *D_LOW* on the *SUE* measure when *IO* equals zero. On the other hand, the coefficient on the interaction between *IO* and *D_LOW* is 0.401, significant at the 1% level with a *t*-value of 2.97. In the second specification, in which I also include the interaction between *SIZE* and *D_LOW*, the coefficient on the interaction between *IO* and *D_LOW* becomes 0.214, significant at the 10% level with a *t*-value of 1.72. The results are similar using the *SUEAF* earnings surprise measure. In the first specification the coefficient of the interaction between *IO* and *D_LOW* is 0.129, significant at the 5% level with a *t*-value of 2.37. When I include the interaction between *SIZE* and *D_LOW* in the second specification, the coefficient becomes 0.093, again significant at 5% level (*t*-value = 1.96).

The positive and significant coefficients on the interaction between *IO* and *D_LOW* in all specifications suggest that the information content of *D_LOW* with respect to earnings surprises decreases as short-selling constraints are reduced as captured by higher levels of *IO*. Moreover, the significant coefficients in the second specifications refute the view that the *IO* effect is simply capturing a firm size effect. On the other hand, the coefficient on the interaction between *SIZE* and *D_LOW* is also positive and significant in both specifications. One potential explanation for this finding is that firm size captures other market frictions such as stock illiquidity that also deter the entry of short sellers into the market and increase the information content of unusually low volume.

B. Exchange-Traded Options as a Proxy for Short-Sale Restrictions

Also following prior literature (e.g., Sorescu (2000), Christophe, Ferri, and Angel (2004), and Boehme, Danielsen, and Sorescu (2006)), the second proxy for short-sale restrictions is the presence of exchange-traded options, *OPTION*.

Table III

The Role of Short-Selling Constraints

The table presents results of quarterly weighted Fama and MacBeth (1973) regressions using two proxies for short-selling constraints. The weights correspond to the number of observations used in each quarterly cross-sectional regression. In Panel A, institutional ownership (*IO*) is used as the measure of short-selling constraints. *IO* is the percentage of shares owned by institutions as reported in 13F filings. In Panel B, the availability of exchange-traded put options is used as the measure of short-selling constraints. *OPTION* takes a value of one if a stock has any exchange-traded put option, and zero otherwise. *OPTION_R* takes a value of one if a stock has an exchange-traded put option and its past 60-day put option volume (from the first day of the event period to last day of the reference period) is not in the bottom 10% of all stocks' put volume in that quarter, and zero otherwise. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. Low (high) unusual volume dummy, *D_LOW (D_HIGH)*, equals one if a stock is classified as a low (high) extreme volume stock and zero otherwise. *SUE*, *SUEAF*, and the remaining control variables are as defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Coefficient estimates are multiplied by 100. Newey and West (1987) t-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Institutional Ownership

	SUE		*SUEAF*	
	(1)	(2)	(3)	(4)
D_LOW	-0.257^{***}	-0.645^{***}	-0.099^{**}	-0.256^{***}
	−3.49	−4.74	−2.57	−3.07
D_HIGH	0.001	0.001	0.002	0.003
	0.01	0.03	0.39	0.44
*D_LOW * IO*	0.401^{***}	0.214^{*}	0.129^{**}	0.093^{**}
	2.97	1.72	2.37	1.96
*D_LOW * SIZE*		0.037^{***}		0.013^{***}
		3.40		3.32
SIZE	-0.052^{**}	-0.061^{***}	0.009^{***}	0.007^{**}
	−2.41	−2.77	3.30	2.48
IO	−0.276	−0.233	0.063^{**}	0.068^{***}
	−1.60	−1.37	2.54	2.74
BK	-0.242^{***}	-0.241^{***}	-0.048^{***}	-0.048^{***}
	−3.80	−3.79	−4.11	−4.12
RET_50	1.983^{***}	1.984^{***}	0.453^{***}	0.452^{***}
	11.17	11.16	7.02	7.02
RET_5	2.633^{***}	2.627^{***}	0.670^{***}	0.666^{***}
	9.67	9.66	5.32	5.32
IVOL	4.606	4.582	-1.609^{***}	-1.609^{***}
	0.88	0.88	−2.96	−2.98
LAG_SURPRISE	9.060^{***}	9.056^{***}	10.12^{***}	10.12^{***}
	13.87	13.88	15.4	15.4
TURN_50	0.037	0.037	−0.007	−0.007
	0.56	0.56	−1.00	−1.00
Constant	0.754^{***}	0.849^{***}	-0.173^{***}	-0.145^{***}
	2.61	2.89	−3.33	−2.72
Adj. R^2	7.3%	7.3%	7.7%	7.7%
# of firm-quarter obs.	256,864		111,510	
Sample period	1980:Q2–2011:Q4 (127 quarters)		1987:Q1–2011:Q4 (100 quarters)	

(*Continued*)

Table III—*Continued*

Panel B: Availability of Exchange-Traded Put Options

	SUE			
	(1)	(2)	(3)	(4)
D_LOW	−0.175***	−0.601**	−0.166***	−0.514**
	−3.21	−2.24	−3.22	−2.45
D_HIGH	−0.046	−0.046	−0.046	−0.045
	−0.74	−0.73	−0.75	−0.71
OPTION	−0.252***	−0.228***		
	−4.67	−4.77		
*D_LOW * OPTION*	0.203**	0.122		
	2.29	1.54		
OPTION_R			−0.277**	−0.261***
			−4.80	−5.09
*D_LOW * OPTION_R*			0.23**	0.163**
			2.57	2.32
SIZE	−0.041	−0.050	−0.038	−0.045
	−1.16	−1.38	−1.11	−1.23
*D_LOW * SIZE*		0.036*		0.029*
		1.87		1.94
IO	−0.314	−0.318	−0.326	−0.331*
	−1.38	−1.41	−1.44	−1.73
BK	−0.175*	−0.175*	−0.177*	−0.176
	−1.74	−1.74	−1.76	−1.59
RET_50	1.763***	1.763***	1.757***	1.756***
	6.29	6.28	6.33	5.59
RET_5	2.137***	2.125***	2.148***	2.139***
	5.76	5.77	5.74	5.44
IVOL	11.06	11.03	11.05	11.03
	1.30	1.30	1.30	1.29
LAG_SURPRISE	7.764***	7.761***	7.771***	7.771***
	17.26	17.16	17.27	17.40
TURN_50	0.137	0.137	0.139	0.140
	1.25	1.24	1.24	1.26
Constant	0.660	0.770*	0.613	0.698
	1.47	1.66	1.44	1.50
Adj. R^2	6.3%	6.3%	6.3%	6.3%
# of firm-quarter observations	149,608			
Sample period	1996:Q2–2011:Q4 (63 quarters)			

When short sellers are restricted from trading in the stock market, they can still trade on their negative information through options. Therefore, when stocks have exchange-traded options, short sellers are not forced to stay by the sidelines. We should thus see a weaker relation between unusually low volume and earnings surprises.

I use two dummy variables to capture the availability of exchange-traded put options, namely, *OPTION* and *OPTION_R*. The first dummy, *OPTION*, takes a value of one if a stock has any exchange-traded put option. The second dummy takes into account the trading volume of the put option. In particular, the *OPTION_R* dummy takes a value of one if a stock has an exchange-traded put option and its put option volume in the past 60 days (from the first day of the event period to last day of the reference period) is not in the bottom 10% of all stocks' put volume in that quarter.[22] Since traders use put options to trade on their negative information, this second measure eliminates stocks with a thinly traded put option, and thus ensures that the stock has enough liquidity in its put option to make it easy for traders to act on their negative information in the options market.

Data on the presence of exchange-traded options, which come from OptionMetrics, are available as of 1996. Therefore, for this analysis the sample period is limited to 1996 to 2011.

It turns out that most of the predominantly large firms in the *SUEAF* sample have exchange-traded options, particularly toward the end of the sample period. Therefore, this analysis is conducted only for the *SUE* sample.

The results are presented in Panel B of Table III. Similar to the analysis in Panel A using *IO*, I include interaction terms to examine the role of *OPTION* and *OPTION_R* with respect to the information content of *D_LOW*. For both definitions of put option availability, I run specifications with and without the *SIZE* interaction. The coefficients on the interactions between the option dummies and *D_LOW* (columns (1) and (3)) are positive and significant without any *SIZE* interactions included. When I include the *SIZE* interactions in column (2), the coefficient on the interaction between the option dummy and unusually low volume (*D_LOW * OPTION*) is still positive but becomes insignificant (*t*-value = 1.54). In contrast, the coefficient on the interaction between the option dummy and unusually low volume is 0.163 and significant at the 5% level when I use the more restricted definition of option availability (*OPTION_R*). Hence, while the presence of options attenuates the effect of *D_LOW* on an earnings surprise, the relation becomes more significant with respect to the *SIZE* effect when the measure of put options takes into account the volume in put options. Overall, these results suggest that the relation between the unusually low volume dummy, *D_LOW*, and earnings surprises is significantly more pronounced among stocks without exchange-traded options.

In summary, the findings in Panels A and B of Table III indicate that the relation between low volume shocks and fundamental information is more pronounced among stocks that are subject to more binding short-sale restrictions, as measured by low institutional ownership or the absence of options. This evidence complements previous findings and strengthens the conclusion that, under more binding short-sale constraints, an unusually low level of trading volume suggests that bad news has yet to arrive to the market, as investors with negative information are forced to stay by the sidelines.

[22] The results are similar if I use 2.5% and 5% cutoff points.

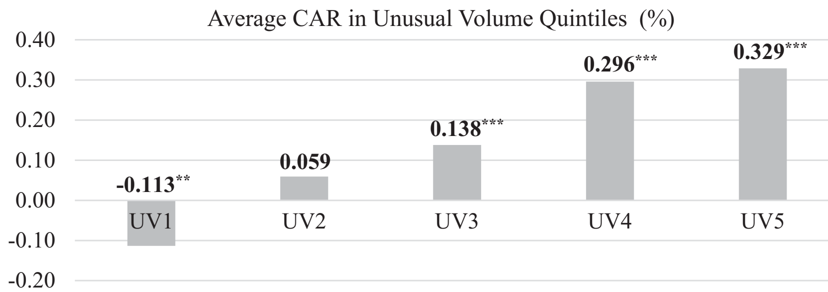

Figure 2. Average cumulative abnormal return (*CAR*) by unusual volume quintiles. The figure presents time-series averages of quarterly mean values of cumulative abnormal returns (*CAR)* within unusual volume quintiles. The weights are based on the number of observations in each unusual volume quintile each quarter. Every quarter stocks are classified into unusual volume quintiles (UV1–UV5) based on their event period volume's rank, defined as average turnover over the [−2,−6] window prior to the earnings announcement, compared to their own past 10-week volume measured over the reference period [−12,−61] window prior to the earnings announcement date. All samples contain common stocks listed on the NYSE, AMEX, and NASDAQ. There are 366,454 stock-quarter observations over the sample period 1980:Q2 to 2011:Q4 (127 quarters). *CAR* is defined as the compounded return over the [−1, +1] window around the earnings announcement date in excess of the compounded value-weighted market return (in %). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

IV. Unusually Low Volume and Earnings Announcement Returns

In financial markets, the main incentive of informed agents to trade on their information is to earn a return on price moves. When new information about a firm arrives to the market via an announcement, stock prices converge to a new equilibrium price that reflects this new information. Therefore, when the negative information that short sellers possess but cannot trade on due to short-selling restrictions is revealed in an earnings announcement, the price should decrease toward the new equilibrium price to reflect this new information. The analysis above using the two earnings surprise measures demonstrates that unusually low volume contains negative information about firm fundamentals that cannot be explained by visibility or risk-based arguments. However, to ensure that unusually low volume signals information that is yet to be incorporated into prices, one also needs to show that unusually low volume predicts announcement returns in a direction consistent with the fundamental information. In this section, I examine this issue by focusing on the relation between unusually low volume and stock returns around earnings announcements.

A. Cumulative Abnormal Returns around Earnings Announcements

I start my analysis by examining the relation between unusually low volume and abnormal returns (*CAR*) around earnings announcements. As before, I begin with portfolio analysis and classify stocks into quintiles based on unusual volume. In Figure 2, I present the time-series averages of quarterly cross-sectional mean cumulative abnormal returns for each unusual volume quintile. Figure 2 reveals a monotonic relation between *CAR* and unusual volume shocks. The mean *CAR* for stocks with low unusual volume (UV1) is −11.3 basis points, significant at the 5% level, over the three days around the announcement. This evidence shows that low volume stocks tend to experience bad news and negative abnormal returns around earnings announcements, even when they are not compared with any other group. When I examine the other groups, the average *CAR* increases to 13.8 basis points for the middle unusual volume category (UV3) and to 32.9 basis points for the high unusual volume category (UV5). The difference in the mean *CAR* between the low volume and the middle volume stock categories is −25.1 basis points, which is significant at the 1% level. Likewise, the difference in the mean *CAR* between the middle and high unusual volume categories is 19.1 basis points, which is again significant at the 1% level. Finally, when low and high volume stocks are compared, the difference in mean *CAR*s is a significant 44.2 basis points.[23]

In more formal analysis, I use quarterly weighted Fama and MacBeth (1973) regressions in which the dependent variable is the *CAR*. The results are presented in Table IV. The first column in Table IV presents the results for the main sample, which corresponds to those in Panel C of Table I. In the second and third columns, I repeat the regression analysis on the *SUE* and *SUAEF* samples, respectively. This approach ensures that unusually low volume predicts abnormal returns in samples for which I document a relation between low volume and fundamental information. The coefficient on *D_LOW* is negative and significant in all samples. Thus, when compared with normal or high volume stocks, unusually low volume stocks are associated with lower abnormal returns around earnings announcements.

On the other hand, an interesting pattern also emerges among the coefficients of the unusually high volume dummy, *D_HIGH*. The coefficients on *D_HIGH* are positive and highly significant, suggesting that unusually *high* volume is also related to *higher* abnormal returns around earning announcements. Given the evidence above that high volume shocks are not predictive of any information about earnings surprises when surprises are measured using unexpected earnings, it is unlikely that this positive and significant relation is driven by value-relevant information content of high volume shocks. Rather, a

[23] Although these differences in *CAR* are both economically and statistically significant, the profits implied by these hedge portfolio results are not attainable. Using reasonable transaction costs based on actual relative effective spreads for that stock-day and short selling costs, I find that the transaction costs exceed the returns over the three-day event window. For this test, I assume that effective spreads reflect actual round trip transactions costs and that short sales incur an additional cost. The analysis over the three-day window shows that, although short sellers have information, returns net of transaction costs are not positive over the three-day window. Net returns become positive when the position is held longer. For example, net returns over the 50 days from day −1 to day +48 are significantly positive. Depending on the risk adjustment and transaction cost estimates, the annualized profits range from 0.82% to 3.43%. The profitability of the strategy over longer horizons suggests that the adjustment of prices to short sellers' information takes longer than three days and hence one needs to hold the stocks long enough to profit from the strategy.

Table IV
Unusually Low Volume and Returns around Earnings Surprises

The table presents results of quarterly weighted Fama and MacBeth (1973) regressions using three-day cumulative abnormal returns, *CAR*, as the dependent variable. The weights correspond to the number of observations used in each quarterly cross-sectional regression. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. *CAR* is defined as the compounded return over the [−1, +1] window around the earnings announcement date in excess of the compounded value-weighted market return. In column (1), I present the results for the entire sample. In column (2), the results are presented only for stocks included in the *SUE* sample. In column (3), only stocks in the *SUEAF* sample are included. A stock is classified as a low (high) extreme volume stock if its event period volume, defined as average turnover over the [−6,−2] window prior to the earnings announcement, is among the bottom (top) 20% of the 10-week reference period volume over the [−61,−12] window prior to the earnings announcement date. Low unusual volume dummy, *D_LOW*, equals one if a stock is classified as a low extreme volume stock and zero otherwise. Similarly, high unusual volume dummy, *D_HIGH*, equals one if a stock is classified as a high extreme volume stock and zero otherwise. The remaining control variables are defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Coefficient estimates are multiplied by 100. Newey and West (1987) *t*-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: *CAR* [−1, +1]		
	All Stocks (1)	*SUE* Sample (2)	*SUEAF* Sample (3)
D_LOW	−0.293***	−0.261***	−0.241***
	−7.13	−5.44	−3.24
D_HIGH	0.292***	0.246***	0.207***
	6.93	4.45	2.88
SIZE	−0.074***	−0.053**	−0.020***
	−3.57	−2.57	−0.92
BK	0.074***	0.100***	0.034
	3.00	2.99	1.19
RET_50	−0.029	−0.070	−0.082
	−0.20	−0.36	−0.52
RET_5	−8.578***	−8.462***	−8.801***
	−12.47	−13.27	−14.17
IO	1.073***	0.928***	1.160***
	7.29	6.51	5.88
IVOL	−1.070	−0.401	−1.649
	−0.51	−0.25	−0.45
LAG_SURPRISE	2.628***	2.360***	1.295***
	6.63	6.13	2.61
TURN_50	−0.324***	−0.265***	−0.152*
	−7.69	−5.66	−1.86
Constant	1.058***	0.818***	0.137
	3.66	3.02	0.39
Adj. R^2	1.5%	1.5%	1.8%
# of firm-quarter obs.	366,454	256,864	111,510
Sample period	1980:Q2–2011:Q4 (127 quarters)	1980:Q2–2011:Q4 (127 quarters)	1987:Q1–2011:Q4 (100 quarters)

more plausible explanation is that the high volume shocks immediately before earnings announcements increase stocks' visibility and create demand shocks that in turn increase the return around the announcement date (Miller (1977)) in a way that is largely value-irrelevant.

B. Alternative Definitions of Abnormal Returns around Earnings Announcements

In this section, I assess the robustness of the findings in Table IV by repeating the return analysis using alternative definitions of abnormal returns around earnings announcements. I present the results only for the main sample as the results are similar if I use the *SUE* or *SUEAF* samples. The results are presented in Table V.

First, since I measure returns over a short horizon of three days, I consider whether the observed returns are due to bid-ask bounce, which is related to market microstructure biases, rather than to real price adjustments due to the arrival of new information. To do so, I repeat my analysis using quote midpoints to calculate abnormal returns around earnings announcements. Since the daily returns in CRSP are calculated using daily market close-to-close prices, and day −1 closing prices overlap with the unusual volume measurement period, I calculate abnormal returns from the opening quote midpoint on day −1 to the closing quote midpoint on day +1. Quotes data come from the TAQ database and are available as of 1993. I apply the same filters as before. To eliminate the effect of outliers and stale price issues, I exclude the top and bottom 1% of midquote returns from the sample. The results are documented in column (1) of Table V, and show that the coefficient on *D_LOW* is negative and significant. This finding suggests that unusually low volume predicts returns net of bid-ask bounce, and thus the results above are robust to concerns arising from bid-ask bounce.

Second, I use alternative risk adjustment methods to ensure that the results are not driven by a failure to adjust for risk. In particular, I employ the CAPM or the Fama-French model augmented with a momentum factor following Brennan, Chordia, and Subrahmanyam (1998). For each stock, using the 66-day (−67,−2) window prior to earnings announcement, I estimate the factor loadings with respect to either the CAPM or the Fama-French model augmented with a momentum factor.[24] The daily Fama-French factors come from Kenneth French's Web site. The risk-adjusted abnormal return is calculated as the return in excess of the factors times the factor loadings for each stock over the three-day window around earnings announcements. The results are presented in columns (2) and (3) of Table V. The coefficients on *D_LOW* are negative and significant in both specifications, and thus the results are robust to adjusting the returns for risk.

[24] I obtain similar results if I use Dimson (1979) betas with one lag. I also use the Fama and French (1993) three-factor model to adjust for risk and obtain similar results.

Table V

Unusually Low Volume and Returns around Earnings Surprises: Alternative Return Definitions

The table presents the results of quarterly weighted Fama and MacBeth (1973) regressions using various definitions of abnormal returns as the dependent variables. The weights correspond to the number of observations used in each quarterly cross-sectional regression. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. In column (1), return is defined as the return from the opening quote midpoint on day −1 to the closing quote midpoint on day +1 in excess of value-weighted market return. In columns (2) and (3), I used risk-adjusted abnormal returns where risk adjustment is done with respect to the CAPM or Fama-French three-factor model augmented with momentum. In column (4), each quarter, I delete the stocks with the top and bottom 1% abnormal return defined as the compounded return over the [−1, +1] window around the earnings announcement date in excess of compounded value-weighted market return. In column (5), abnormal return is defined as the compounded return over the [0, +1] window around the earnings announcement date in excess of the compounded value-weighted market return. A stock is classified as a low (high) extreme volume stock if its event period volume, defined as average turnover over the [−6,−2] window prior to the earnings announcement, is among the bottom (top) 20% of the 10-week reference period volume over the [−61,−12] window prior to the earnings announcement date. Low unusual volume dummy, *D_LOW*, equals one if a stock is classified as a low extreme volume stock and zero otherwise. Similarly, high unusual volume dummy, *D_HIGH*, equals one if a stock is classified as a high extreme volume stock and zero otherwise. Coefficient estimates on the control variables have been omitted to conserve space. Coefficient estimates are multiplied by 100. Newey and West (1987) *t*-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Mid-Quote Return (from Day[−1] Open Mid-Quote to Day [+1] Closing Mid-Quote)	Risk Adjustment		Controlling for Outliers	Alternative Return Measurement Window [0, +1]
		CAPM	FF4		
	(1)	(2)	(3)	(4)	(5)
D_LOW	-0.201^{***}	-0.290^{***}	-0.272^{***}	-0.252^{***}	-0.167^{***}
	−3.23	−7.29	−7.16	−6.42	−5.96
D_HIGH	0.057	0.280^{***}	0.269^{***}	0.232^{***}	0.116^{***}
	0.99	6.52	6.23	5.20	3.91
Other control variables	Omitted	Omitted	Omitted	Omitted	Omitted
Adj. R^2	1.5%	1.4%	1.5%	1.6%	1.5%
# of firm-quarter obs.	203,368	366,454	366,454	359,257	366,454
Sample period	1993:Q2–2011:Q4 (75 quarters)			1980:Q2–2011:Q4 (127 quarters)	

Third, to ensure that the results are not driven by a few outliers in the cross-sectional regressions each quarter, I eliminate stocks with the lowest and highest 1% of *CAR* from the sample. The results are presented in column (4) of Table V, and show that the relation between *D_LOW* and returns around earnings surprises is robust to excluding outliers from the cross-sectional regression analysis.

Finally, I skip a day between the unusual volume measurement period and the reference period, and measure abnormal returns over the [0, +1] window around earnings announcements. The results are presented in column (5) in Table V, and show that the relation between unusually low volume and returns is robust to this alternative return measurement window.

C. The Relation between Return Predictability and Fundamental Value Predictability

In Tables IV and V, I show that both unusually low and unusually high volume shocks predict returns around earnings surprises. I argue that the return predictability of unusually *low* volume shocks around earnings surprises is related to fundamental information, while the return predictability of *high* volume shocks is due to non-information-related dynamics such as an increase in visibility. This argument is supported by findings in Section II that unusually low volume contains negative information about firm fundamentals, as measured by unexpected earnings, and that such information content is not present in unusually high volume shocks. In this section, I present further evidence that reinforces the view that the return predictability of unusually low volume—but not high volume—is related to fundamental value predictability.

Specifically, I replicate the Fama and MacBeth (1973) regressions in Table IV in which the dependent variable is the three-day cumulative abnormal return around earnings announcements. The sample consists of stocks that remain in the sample after all the restrictions in all three earnings surprise samples are imposed. I run regressions with and without the earnings-based fundamental information variables, *SUE* and *SUAEF*, as additional independent variables, and I compare the coefficients on unusual volume shocks, *D_LOW* and *D_HIGH*, between these two specifications. If the relation between unusually low volume and returns around earnings surprises is driven by the negative information content of unusually low volume about firm fundamentals, then the coefficient on the unusually low volume dummy should be significantly lower in magnitude after controlling for unexpected earnings. In contrast, since unusually high volume shocks are not related to value-relevant information, inclusion of the *SUE* and *SUEAF* measures should not affect the coefficient on the high unusual volume dummy.

Column (1) in Table VI provides results of the baseline regression model, which does not include the fundamental variables *SUE* and *SUEAF*. The coefficient on the unusually low volume dummy, *D_LOW*, is -0.210 (t-value $=$ -3.14), and the coefficient on unusually high volume dummy is 0.152 (t-value $=$ 2.03). These coefficients confirm that unusually high and low volume shocks predict abnormal returns around earnings announcements. When I add the fundamental information variables *SUE* and *SUEAF* in column (2), the coefficients on both variables are positive and highly significant. More importantly, the coefficient on *D_LOW* decreases (in magnitude) to -0.146 and the significance level drops from 1% to 10% (t-value $=$ -1.91). The difference between coefficients on *D_LOW* in columns (1) and (2) is highly significant with a t-value of -2.97. Comparing the magnitude of these coefficients, the results suggest that approximately 30% of the ability of unusually low volume

Table VI

The Relation between Return Predictability and Fundamental Value Predictability

The table presents the results of quarterly weighted Fama and MacBeth (1973) regressions using three-day cumulative abnormal returns, *CAR*, as the dependent variables. The weights correspond to the number of observations used in each quarterly cross-sectional regressions. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. *CAR* is defined as the compounded return over the [−1, +1] window around the earnings announcement date in excess of the compounded value-weighted market return. In column (1), I present the results with the standard control variables. In column (2), *SUE* and *SUEAF* earnings surprises are added as additional control variables. In column (3), only stocks in the *SUEAF* sample are included. *SUE* is standardized unexpected earnings defined as the difference in EPS before extraordinary items between quarters q and $q-4$ divided by the $q-4$ quarter-end price. *SUEAF* is the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by the $q-4$ quarter-end price. A stock is classified as a low (high) extreme volume stock if its event period volume, defined as average turnover over the [−6,−2] window prior to earnings announcement, is among the bottom (top) 20% of the 10-week reference period volume over the [−61,−12] window prior to the earnings announcement date. Low unusual volume dummy, *D_LOW*, equals one if a stock is classified as a low extreme volume stock and zero otherwise. Similarly, high unusual volume dummy, *D_HIGH*, equals one if a stock is classified as a high extreme volume stock and zero otherwise. The remaining control variables are as defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Coefficient estimates are multiplied by 100 except for *SUE* and *SUEAF*. Coefficient estimates on the control variables have been omitted to conserve space. Newey and West (1987) t-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: *CAR* [−1, +1]	(1)	(2)	Difference in Coefficients (2) − (1)
D_LOW	−0.210***	−0.146*	0.064***
	−3.14	−1.91	−2.97
D_HIGH	0.152**	0.152**	0.000
	2.03	2.15	0.26
SUEAF		2.81***	
		11.67	
SUE		0.095***	
		6.80	
Other control variables	Omitted	Omitted	
Adj. R^2	1.83%	6.66%	
# of firm-quarter obs.	102,674		
Sample period	1987:Q1–2011:Q4 (100 quarters)		

to predict abnormal returns can be explained by the predictive power of *SUE* and *SUEAF* surprises.[25] In contrast, the coefficients on the unusually high volume dummy, *D_HIGH*, is 0.152 (t-value = 2.15) in columns (1) and (2), and

[25] Obviously, the *SUE* and *SUEAF* measures do not account for all the fundamental information revealed at the earnings announcements. The negative and significant coefficient on *D_LOW* in the second specification simply represents the additional fundamental information not captured by *SUE* and *SUEAF* that is captured by *CAR*.

the difference between coefficients on *D_ HIGH* in columns (1) and (2) is not significant. Therefore, controlling for fundamental information, as measured by *SUE* and *SUEAF*, does not significantly affect the coefficient on *D_HIGH*.

Overall, the findings in Table VI confirm the view that the return predictability of unusually low volume shocks, but not high volume shocks, around earnings surprises is related to the predictability of fundamental information.

V. Information Content of Unusually Low Volume: Additional Evidence

In this section, I use short sellers' trading activity and news around earnings surprises to provide additional evidence on the information argument.

A. Short Sellers' Trading Activity and Information Content of Unusually Low Volume

When short sellers trade on their negative information about earnings surprises, their trades should signal the negative information they possess. In this case, since short sellers' trading already signals their information, greater short-seller trading should reduce the information content of unusually low volume about earnings surprises. In this section, I use monthly short interest and put option volume to examine the effect of short sellers' trading activity on the relation between unusually low volume and earnings surprises.

A.1. Short Interest as a Measure of Short Sellers' Trading Activity

I measure short sellers' trading using monthly short interest. Short interest is defined as the ratio of total shares shorted to total shares outstanding in the middle of the month prior to the earnings announcement. Data on short interest are available as of the fourth quarter of 1988, which yields a total of 93 quarters for the analysis.[26] To control for the effect of firm size on the level of short interest, I closely follow Chen et al. (2008)[27] and regress the log of monthly short interest plus 0.01%, log (short interest + 0.01%), on 20 dummy variables corresponding to quintiles of the NYSE market-cap distribution in each quarter.[28] I then use the residual short interest, *SHORT*, obtained from this quarterly regression in my analysis. I apply the same filters as in the main

[26] The short data are available from June 1988. However, I skip the third quarter of 1988 since data are not available for earnings announcements in June 1988. Results are similar if I do not skip the third quarter of 1988.

[27] As Chen et al. (2008) show, there is an inverted U-shape relation between short interest and firm size—it is lower among microcap and big firms and higher among medium-sized firms. Therefore, simply including another interaction term with size would not properly account for the size effect. Also, since the raw short interest data are strongly right-skewed, I apply a log transformation.

[28] The NYSE market-cap quintiles are obtained from Kenneth French's data library available from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

sample, and I exclude the bottom and top 1% of residuals to ensure that outliers do not drive the results.

To test the prediction above on the impact of short sellers' trading on the information content of unusually low volume about earnings surprises, I perform quarterly weighted Fama-MacBeth regressions including residual short interest, *SHORT*, and its interaction with unusually low volume as additional independent variables. According to the information story, there should be a negative and significant coefficient on *SHORT*, while the coefficient on the interaction term should be positive and significant. The results are presented in Table VII.

For all three earnings surprise measures in Table V, there is a negative and significant relation between residual short interest, *SHORT*, and earnings surprises. The negative coefficients on *SHORT* are consistent with the idea that short sellers can successfully predict upcoming earnings surprises.[29] More importantly, the coefficients on the interaction term between *SHORT* and *D_LOW* are positive and significant at the 1% and 5% levels for *CAR* and *SUE*, respectively. The positive and significant coefficients support the view that the relation between unusually low volume and earnings surprises is significantly less pronounced among stocks with higher short-selling activity. Surprisingly, in the *SUAEF* sample, although the coefficients on short interest and unusually low volume are both negative and significant, the interaction term is not significant and carries a negative sign. Hence, within the *SUEAF* sample, I do not find evidence in support of my conjecture.

A.2. Put Option Trading as a Measure of Short Sellers' Trading Activity

When short sellers choose to trade in the options market, put option volume should increase and this abnormal put option volume should signal the negative information that short sellers possess about upcoming earnings announcements. Therefore, in stocks with higher abnormal put option volume prior to earning announcements, the information content of unusually low volume about negative earnings surprises should be lower, since short sellers' information no longer stays by the sidelines. In this section, I test this argument by examining the information content of abnormal put option trading activity about upcoming earnings surprises, and the effect of such information content on the relation between unusually low volume and earnings surprises.

Unusual put option volume, *UN_PUT*, is defined as the ratio of a stock's event period put option volume to its previous 10-week reference period put option volume where event and reference periods are defined as before. Unusual call option volume, *UN_CALL*, is defined similarly. To eliminate the effect of outliers, I transform the unusual option volumes into decile ranks that take a value between zero and one.

[29] Christophe, Ferri, and James (2004) and Akbas et al. (2014) also present evidence that short sellers are informed about the outcome of earnings announcements.

Table VII

Short Interest, Unusually Low Volume, and Earnings Surprises

The table presents results of quarterly weighted Fama and MacBeth (1973) regressions using the *CAR*, *SUE*, and *SUEAF* measures of earnings surprises as the dependent variables. The weights correspond to the number of observations used in each quarterly cross-sectional regression. All samples contain common stocks listed on the NYSE and NASDAQ. A stock is classified as a low (high) extreme volume stock if its event period volume, defined as average turnover over the [−6,−2] window prior to earnings announcement, is among the bottom (top) 20% of the 10-week reference period volume over the [−61,−12] window prior to the earnings announcement date. Low unusual volume dummy, *D_LOW*, equals one if a stock is classified as a low extreme volume stock and zero otherwise. Similarly, high unusual volume dummy, *D_HIGH*, equals one if a stock is classified as a high extreme volume stock and zero otherwise. Monthly short interest is defined as the total shares shorted divided by the total shares outstanding measured at the middle of each month prior to the earnings announcement. *SHORT* is the residual short interest obtained from regressing log of short interest plus 0.01% on 20 dummy variables corresponding to demi-deciles of the NYSE market-cap distribution in each quarter. *CAR*, *SUE*, *SUEAF*, and the remaining control variables are as defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Coefficient estimates are multiplied by 100. Newey and West (1987) t-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR (1)	*SUE* (2)	*SUAEF* (3)
D_LOW	-0.322^{***}	-0.064^{**}	-0.017^{***}
	−6.50	−2.25	−3.55
SHORT	-0.155^{***}	-0.124^{***}	-0.015^{***}
	−6.22	−3.27	−3.43
D_LOW SHORT*	0.077^{***}	0.083^{**}	−0.010
	2.93	1.97	−1.19
D_HIGH	0.310^{***}	0.013	0.006
	6.16	0.23	1.06
SIZE	-0.048^{**}	-0.055^{*}	0.006^{***}
	−2.07	−1.77	2.62
IO	1.417^{***}	−0.110	0.094^{***}
	9.17	−0.73	5.23
BK	0.084^{***}	-0.221^{***}	-0.045^{***}
	2.61	−2.98	−5.46
RET_50	0.006	1.875^{***}	0.425^{***}
	0.04	8.37	9.20
RET_5	-9.150^{***}	2.384^{***}	0.612^{***}
	−12.97	7.00	7.35
IVOL	0.292	7.165	-1.565^{***}
	0.11	1.09	−3.57
LAG_SURPRISE	2.026^{***}	7.736^{***}	10.15^{***}
	4.96	19.12	13.83
TURN_50	-0.190^{***}	0.148	0.007
	−4.10	1.62	1.03
Constant	0.416	0.536	-0.169^{***}
	1.22	1.59	−4.18
Adj. R^2	1.57%	6.54%	7.70%
# of firm-quarter obs.	274,587	198,631	105,488
Sample period		1988:Q4–2011:Q4 (93 quarters)	

Data on option volumes come from Optionmetrics, and are available as of 1996. To be consistent with the analysis in Section IIIB.I skip the first quarter of 1996. This procedure yields a total of 63 quarters in the sample. I apply the same filters as in the main sample, and I also require nonmissing put and call option volumes over the event and reference periods. To ensure that the results are not driven by stocks with thinly traded options, I delete the bottom 5% of stocks based on total option volume over the reference period.

The results of the quarterly weighted Fama and MacBeth (1973) regression analysis are presented in Table VIII. For all three earnings surprise measures, in addition to the same set of control variables and the dummies for unusual stock volume, I include the unusual put and call option volumes and their interactions with unusually low volume.

The coefficients on unusual put option volume, *UN_PUT*, are negative and significant at the 1% level for the *CAR* and *SUAEF* samples. This finding is in line with the idea that, when traders with negative information choose to trade using put options, their trades are informative about upcoming earnings surprises.

The main results of interest are the coefficients on the interaction terms. The coefficients on the interaction between *UN_PUT* and *D_LOW* are 0.746 and 0.052, significant at the 1% (t-value = 2.74) and 5% (t-value = 2.21) levels, for the *CAR* and *SUAEF* samples, respectively. The interaction coefficient for the *CAR* sample indicates that, while the coefficient on *D_LOW* is −0.397 (t-value = −2.45) for stocks in the bottom decile of unusual put option volume, the coefficient increases to an insignificant 0.349 for stocks in the top decile of unusual put volume. In other words, the negative relation between unusually low volume and abnormal returns around earnings surprises, *CAR*, disappears when abnormal put option volume increases. Similar results obtain for the *SUAEF* sample. These results are in line with the idea that, when informed agents choose to trade on their negative information in the options market, the informativeness of unusually low volume significantly decreases. In the *SUE* sample, however, the coefficient on *UN_PUT* remains negative with a t-value of −1.49, suggesting that the information content of unusually high put option volume is weaker for this sample. Moreover, the coefficients on *D_LOW* and its interaction with *UN_PUT* are also insignificant. Together with the findings in Panel B of Table III, these findings suggest that, among optioned stocks, short sellers' information regarding SUE does not stay on the sidelines in the stock market.

In contrast, the coefficients on unusually high call option volume *UN_CALL*, are positive and significant. This finding suggests that the options market, perhaps for reasons such as the use of leverage, is also a preferred venue for informed traders when they trade on their positive information. Since the information argument does not have any prediction for the coefficient on *UN_CALL*, this positive and significant relation has no impact on my findings. However, when we examine the interaction between abnormal call option volume, *UN_CALL*, and *D_LOW*, the coefficients are not significant and the signs are not consistent across the different surprise measures. Therefore, although

Table VIII

Option Volume, Unusually Low Volume, and Earnings Surprises

The table presents the results of quarterly weighted Fama and MacBeth (1973) regressions using the *CAR*, *SUE*, and *SUEAF* measures of earnings surprises as the dependent variables. The weights correspond to the number of observations used in each quarterly cross-sectional regression. All samples contain common stocks listed on the NYSE, NASDAQ, and Amex. Unusual put option volume, *UN_PUT*, is defined as the ratio of event period put option volume to the 10-week reference period put option volume. Unusual call option volume, *UN_CALL*, is computed similarly. Both measures are transformed into decile ranks to take a value between zero and one. *CAR*, *SUE*, *SUEAF*, and the remaining control variables are as defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Coefficient estimates are multiplied by 100. Newey and West (1987) t-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR (1)	*SUAEF* (2)	*SUE* (3)
D_LOW	−0.397**	−0.039**	0.223
	−2.45	−2.28	1.04
D_HIGH	0.057	−0.005	−0.016
	0.55	−1.00	−0.38
UN_PUT	−0.367***	−0.033***	−0.088
	−2.69	−3.63	−1.49
*UN_PUT * D_LOW*	0.746***	0.052**	−0.312
	2.74	2.21	−0.90
UN_CALL	0.326 **	0.043***	0.179*
	2.15	4.77	1.94
UN_CALL D_LOW*	−0.244	0.021	−0.153
	−0.91	0.96	−1.36
SIZE	0.010	0.002	−0.035
	0.26	1.19	−0.70
BM	0.019	−0.011*	−0.152
	0.35	−1.77	−1.09
RET_50	−0.195	0.284***	1.343**
	−0.74	7.92	2.22
RET_50	−6.870***	0.256***	1.054***
	−8.15	5.23	3.61
IO	1.848 ***	0.052***	−0.075
	7.64	2.69	−0.29
IVOL	−2.351	−0.225	8.738
	−0.62	−0.64	1.11
LAG_SURPRISE	0.390	9.306***	8.129***
	0.56	11.53	13.68
TURN_50	−0.276***	0.006	0.123
	−2.51	0.87	0.87
Constant	−0.441	−0.041	0.260
	−0.79	−1.20	0.35
Adj. R^2	1.9%	6.4%	7.1%
# of firm-quarter obs.	75,590	48,359	64,416
Sample period	1996:Q2–2011:Q4 (63 quarters)	1996:Q2–2011:Q4 (63 quarters)	1996:Q2–2011:Q4 (63 quarters)

call option volume has its own positive information content for future earnings surprises, it does not have significant effect on the relation between unusually low volume, *D_LOW*, and earnings surprises. Given that short sellers are likely to use put options to trade on their negative information, the finding that *only* abnormally high put option volume affects the relation further supports the information story.

Overall, the results in Tables VII and VIII provide strong additional evidence to support the idea that unusually low trading volume's information content is highly related to short sellers' ability to trade on their information, further supporting the information story of Diamond and Verrecchia (1987).

B. Unusually Low Volume and Public News around Earnings Announcements

In this section, I examine the relation between unusually low volume prior to an earnings announcement and the sentiment in public news around the announcements. I obtain data on firm-specific public news from Thomson Reuters News Analytics, which are available as of 2003.[30] Thomson collects corporate news items from all public sources, and classifies each item through content analysis according to its relevance, sentiment, novelty, and topic. The sentiment variable measures whether a particular news item contains "good" or "bad" information about the underlying corporation. Analysis of firm-specific news content sheds light on the information content of low volume shocks on earnings surprises, using an alternative measure that is related to information but is not related to the visibility or risk-based arguments.

Thomson provides negative, neutral, and positive sentiment scores for each news item. Each score takes a value from 0 to 100, with the three scores summing to 100. Higher scores in a sentiment category mean that the news is more likely to belong to that category. Using these scores, for each firm I construct two news measures, *NEWS1* and *NEWS2*. To do so, I first create the variable *SENT*, which for each news item takes a numerical value of $+1$, 0, or -1 depending upon sentiment scores. In particular, a value of $+1$ (-1) is assigned to news items with a sentiment score above 50 in the positive (negative) sentiment category; all other news items are assigned a sentiment value of zero. The measure *NEWS1* is then obtained by summing up the *SENT* scores over the $[0, +1]$ announcement window. If a stock does not have a news item over the $[0, +1]$ announcement window, I assume that this absence of news is equivalent to neutral news content and thus I assign *NEWS1* a value of zero. For the second news measure, *NEWS2*, I use the average negative news items' sentiment score provided by Thomson over the $[0, +1]$ announcement window. Again, if a stock does not have a news item over the $[0, +1]$ announcement window, I assign this measure a value of zero. To make the inferences from both news measures consistent, I multiply *NEWS2* by -1, so that a lower score implies more negative news.

[30] I thank Thomson Reuters News Analytics for providing the news data around earnings announcements.

In addition to applying the same filters as in the earlier analyses, I employ three filters designed to enhance the reliability of these news measures. First, I exclude all news items categorized as "order imbalances" or "stock prices." This screen ensures that the sample news items are not simply mentioning stock price movements that might be due to a change in risk or increase in visibility rather than to fundamental information. This approach alleviates concerns regarding causality between news and stock prices. In other words, the news items I include provide new information to the market, rather than simply mentioning any significant stock price changes that may not be related to fundamental information. Second, to ensure that each news item is indeed about the stock in question, I use the relevance score provided by Thomson. The relevance score takes a value from 0 to 100, where a higher value means that the firm is a more important subject of the original news source. I only include news items that have a relevance score above 50. Third, I use the novelty score of Thomson to eliminate news items repeated in various sources. The novelty score is equal to the number of previous news items over the past 24 hours related to each news item. For example, a novelty score of zero means that the news item is linked to zero other news items over the previous 24 hours. A lower novelty score thus indicates that there is less repetition of a given news item. I require that sample news items have at most one related news item to ensure that I am not simply capturing news that appears in multiple sources, which would inflate the sentiment score associated with any given news item.[31] The final data sample consists of 79,058 stock-quarter observations, for an average of 2,196 stocks per quarter.

I analyze the relation between news content and unusual volume using quarterly weighted Fama and MacBeth (1973) regressions over the 36 quarters since 2003. The results are presented in Table IX. The dependent variables are *NEWS1* and *NEWS2* measured over the [0, +1] event window. I also control for the average news measure over the [−6,−2] preevent window, to ensure that the results are not driven by "news momentum." All control variables are defined as before. I find that there is a negative and significant relation between unusually low volume prior to earnings announcements and the content of public news around the earnings announcements. The coefficient on *D_LOW* is negative for both the *NEWS1* and *NEWS2* measures, and is significant at the 5% and 1% levels, respectively. These results provide additional evidence that unusually low volume prior to earnings announcements signals unfavorable information about earnings outcomes, as measured by the content of public news around the earnings announcements. In contrast, the coefficients on *D_HIGH* do not have consistent signs and are not significant at any acceptable level, which is consistent with the view that the information content in high versus low unusual volume is different.

[31] The results are similar if I require a relevance score above 66, 75, or 99. I also require one or zero linked news items over the past 12 hours for the novelty measure and find similar results.

Table IX

Unusually Low Volume as Predictor of News Sentiment around Earnings Announcements

The table presents results of quarterly weighted Fama and MacBeth (1973) regressions using public news sentiment scores, *NEWS1* and *NEWS*, around earning announcements as the dependent variables. The weights correspond to the number of observations used in each quarterly cross-sectional regression. The sample contains common stocks listed on NYSE, NASDAQ, and Amex over the sample period 2003:Q1 to 2011:Q4 (36 quarters). There are 79,058 stock-quarter observations and on average 2,196 stocks in each quarter. *NEWS1* is the total signed values of news items over the [0, +1] window around earnings announcements. For signed news items, I assign numerical values of +1, 0, and −1 to all news items based on their sentiment score provided by Thomson Reuters. *NEWS2* is the average sentiment score over the [0, +1] window. Days with no news items are assigned an aggregate *NEWS1* (*NEWS2*) measure equal to zero. A stock is classified as a low (high) extreme volume stock if its event period volume, defined as average turnover over the [−6,−2] window prior to earnings announcement, is among the bottom (top) 20% of the 10-week reference period volume over the [−61,−12] window prior to the earnings announcement date. Low unusual volume dummy, *D_LOW*, equals one if a stock is classified as a low extreme volume stock and zero otherwise. Similarly, high unusual volume dummy, *D_HIGH*, equals one if a stock is classified as a high extreme volume stock and zero otherwise. The remaining control variables are as defined in Table I. I apply log transformations to *TURN_50*, *SIZE*, and *BM*. Newey and West (1987) *t*-statistics are reported below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

NEWS Measure	*D_LOW*	*D_HIGH*	*SIZE*	*BK*	*RET_50*	*RET_50*	*IO*	*IVOL*	*LAG_NEWS*	*LAG_SURP.*	*TURN_50*	Cons.	Adj. R^2
NEWS1	−0.028***	−0.002	0.052***	−0.118***	0.085***	0.420***	0.084***	−3.35***	0.133***	1.323***	−0.072***	−0.639***	6.2%
	−2.63	−0.13	3.57	−4.11	2.54	4.20	2.68	−4.80	4.95	4.28	−4.88	−3.73	
NEWS2	−0.178***	0.124	−0.050***	−0.755***	0.893***	2.172***	0.76***	−27.2***	0.240***	7.255***	−0.509***	−6.75***	9.1%
	−1.99	1.23	−0.82	−4.02	2.83	3.07	3.52	−4.73	5.45	4.92	−4.90	−5.18	

VI. Robustness Checks and Alternative Explanations

In this section, I conduct several tests to assess the robustness of the relation between unusually low volume and earnings surprises.

A. Controlling for Financial Distress

I begin by investigating the possibility that the relation between unusually low volume and future changes in firm fundamentals can be explained by financial distress. The idea is that financial distress can cause investors to lose interest in a stock, which can result in low volume and in turn low future fundamentals. To the extent that this story holds, the relation between unusually low volume and future fundamentals should disappear (or significantly weaken) after controlling for financial distress.

To examine this potential explanation, I control for financial distress using Campbell, Hilscher, and Szilagyi's (2008) failure probability measure. In results presented in Table IA.I of the Internet Appendix, I find that, even after controlling for distress, the relation between unusually low volume and earnings surprises remains highly significant. More broadly, including the financial distress measure in the regression analysis does not alter any of the previous inferences. Therefore, financial distress does not appear to be driving the results.[32]

B. Controlling for Order Imbalance and Sidedness Prior to Negative Earnings Surprises

In this section, I control for two trading-related measures of information: trading order imbalance and the sidedness measure of Sarkar and Schwartz (2009).[33] I closely follow Chordia and Subrahmanyam (2004) in calculating order imbalance and Sarkar and Schwartz (2009) in calculating *SIDEDNESS*.[34] Specifically, using data on intraday trades and quotes that come from the TAQ database, I calculate the daily order imbalance as either the number of trades (*OIB_TRADE*) or the number of shares traded (*OIB_SHARE*). I then average the daily order imbalance and sidedness measures over the five-day event period, [−6,−2] to obtain the final measures for each earnings announcement. (Untabulated results are similar if I use the absolute value of the trading order imbalance.)

[32] The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

[33] As mentioned by Sarkar and Schwartz (2009), while sidedness and order imbalance are related (i.e., more sidedness is associated with a lower absolute value of order imbalance), belief dispersion or information asymmetry is reflected in sidedness rather than in imbalance. Hence, these two measures incorporate complementary information, in which case using both should yield insights on different dimensions of the information contained in order flow.

[34] I refer the reader to these papers for further details regarding the calculation of both measures. For each measure, I use the Lee and Ready (1991) algorithm to determine whether a trade is buyer- versus seller-initiated.

As before, I use quarterly weighted Fama and MacBeth (1973) regression analysis. In results presented in Panels A and B of Table IA.II in the Internet Appendix, I find that there is a positive and significant relation between trading order imbalance and earnings surprises. I also find that sidedness negatively predicts the *CAR* measure of earnings surprises but has no information content for the *SUE* and *SUEAF* measures. However, in each of the specifications, the coefficient on *D_LOW* is negative and significant. Moreover, controlling for order imbalance or sidedness does not affect the magnitude of the coefficients on unusually low volume, *D_LOW*. Results are therefore robust to controlling for sidedness or trading order imbalance.

C. Controlling for Outliers

Depending on the surprise measure, the number of quarters ranges from 100 to 127, which might raise concerns that the negative relation between *D_LOW* and earnings surprises may be driven by a few outliers (i.e., quarters with very large negative cross-sectional coefficient estimates on *D_LOW*). Although using weighted least squares alleviates this concern, to further assess robustness of my results to outliers I repeat my analysis after deleting the bottom and top 10% of the coefficients on *D_LOW* obtained from the cross-sectional regressions.[35] The results, presented in Panels A and B of Table IA.III in the Internet Appendix, show that, even after deleting the highest and lowest 10% of coefficients on *D_LOW*, the time-series average of the remaining coefficients is still highly significant. To further ensure that my results are not driven by outliers in the cross-sectional regressions, each quarter I eliminate stocks with the lowest and highest 2% of the surprise measures in each cross-sectional regression. The relation between *D_LOW* and earnings surprises again remains significant. Overall, the results indicate that the relation between unusually low volume and earnings surprises is not driven by outliers.

D. Other Robustness Tests

First, instead of normalizing the *SUEAF* and *SUE* measures using the lagged price, I use the median analyst forecast and lagged earnings, respectively. This yields the earnings surprise measures given as a percentage of the median forecast or past earnings. In addition, instead of calculating *SUE* using the change between quarters q and $q-4$, I repeat the analysis using the average over the past year as the reference point. The results, presented in Table IA.IV, are similar to my original findings.

Second, I repeat the main analysis using dollar volume as Gervais, Kaniel, and Milgelgrin (2001) show that dollar trading volume, measured as the number of shares traded per day times the daily closing share price, also predicts future returns. The results, presented in Panel A of Table IAV, show that the relation between unusually low volume and earnings surprises holds.

[35] I obtain similar results using 5% or 15% cutoffs.

Third, to assess the robustness of the relation between unusually low trading volume and earnings surprises with respect to alternative measurement windows for unusual trading volume, I skip two days between the event period and the announcement period and measure the volume shocks over the [−7,−3] window relative to the earnings announcement date; the reference period is unchanged. The results, presented in Panel B of Table IAV, show that my main findings are robust to alternative measurement windows for unusual trading volume.

E. Unusual Trading Volume and Postearnings Announcement Drift

Another way to distinguish between the information and the visibility hypotheses is to examine the relation between unusual volume and postearnings announcement drift. Vega (2006) shows that postearnings announcement drift disappears among stocks with greater informed trading as measured by Easley and O'Hara's (1992) PIN measure. The evidence thus suggests that the drift is affected by the arrival rate of uninformed versus informed traders (Brav and Heaton (2002)). Applying Vega's arguments to the context of volume shocks, the visibility hypothesis predicts that high volume shocks attract uninformed agents due to increased visibility and create demand shocks that tend to last for up to one month (Gervais, Kaniel, and Milgelgrin (2001)). To the extent that the visibility hypothesis explains the relation between volume shocks (both low and high volume) and future returns, postearnings announcement drift should be higher following high volume shocks due to the arrival of uninformed traders. The information hypothesis, in contrast, suggests no relation between unusual volume and postearnings announcement drift. This is because, under the information hypothesis, low volume shocks signal negative information as informed agents stay by the sidelines, and hence low volume shocks are associated with the arrival of uninformed traders while high volume shocks are likely to attract a large number of uninformed investors. Hence, by sorting stocks into preevent trading volume, we are not (implicitly) sorting them on any informed trader measure that relates to Easley and O'Hara's PIN measure. As a result, to the extent that the information hypothesis holds, we expect to find no relation between preevent volume and postearnings announcement drift. To examine the relation between unusual volume shocks and postearnings announcement drift, I use the same methodology as in Table VIII of Vega (2006). Each quarter, I first sort stocks into unusually low, normal, and high volume categories. Within each category, I further sort stocks into quintiles based on *CAR*, *SUE*, or *SUAEF*. Stocks are then held in their respective portfolios over the 30-day window [+4, +33] following the earning announcement date. Next, for each portfolio, I compute the average abnormal return as the difference between the average stock return and the value-weighted market return.[36]

[36] Results are similar when I use the risk-adjusted return where the risk adjustment is the alpha based on the Fama and French (1993) three-factor model augmented with the momentum factor.

The results, presented in Table IA.VI of the Internet Appendix, show that there is no relation between preannouncement unusual volume and postearnings announcement drift. For example, when earnings surprises are measured using CAR, the average drift for the long-short hedge portfolio is 1.37%, 1.59%, and 1.56% for unusually low, normal, and high volume stocks, respectively. Moreover, the differences in the drift between these groups are not statistically significant. I obtain similar results when I use the *SUE* and *SUEAF* measures. In summary, the results in Table IA.VI strongly support the information hypothesis over the visibility hypothesis.

VII. Conclusion

In this paper, I investigate the information content of unusually low trading volume about changes in firm fundamentals measured using various earnings surprise measures. I find that unusually low trading volume prior to earnings announcements predicts more unfavorable earnings surprises compared to stocks without any unusual trading activity or to stocks with unusually high trading activity. These findings are in line with the theoretical arguments of Diamond and Verrecchia (1987) and suggest that unusually low trading volume conveys negative information since, under short-selling constraints, informed agents stay by the sidelines and cannot trade on their negative information. In other words, the calm before the storm conveys significant unfavorable value-relevant information. In contrast, such a relation does not exist between high unusual volume shocks and future firm fundamentals, suggesting that the underlying reasons for the return predictability of high and low volume shocks are different.

The results are robust to the inclusion of several control variables, alternative definitions of trading activity, various unusual volume measurement periods, and alternative definitions of earnings surprises. Moreover, the results are more pronounced among stocks with higher short-sale restrictions, as proxied by low institutional ownership or the absence of options. In additional analysis I show that, in line with the argument that unusually low volume signals short sellers' information among stocks with higher short-selling activity as measured by monthly short interest, the information content of unusually low volume is significantly lower. I further document that, when short sellers use option markets to trade, put option volume also predicts negative earnings surprises and reduces the information content of unusually low volume. Finally, I show that unusually low volume predicts the content of public news around earnings announcements.

This paper contributes to the ongoing debate on the effect of unusual trading volume on future prices. Unlike previous literature, I focus on unusually low levels of trading volume and uncover an important channel through which low trading volume is negatively associated with future returns. My findings are consistent with the theoretical predictions of Diamond and Verrecchia (1987).

In this paper I focus on the information content of unusually low volume prior to scheduled earnings announcements. Our understanding could be further improved by examining unusual volume prior to unscheduled events such as mergers and acquisitions. Identifying the determinants of unusually low and high volume represents another potentially fruitful area of inquiry. I leave analyses of these and other related questions to future research.

Initial submission: February 26, 2014; Final version received: August 31, 2015
Editor: Kenneth Singleton

REFERENCES

Akbas, Ferhat, Ekkehart Boehmer, Bilal Erturk, and Sorin Sorescu, 2014, Short interest, returns, and fundamentals, Working paper, University of Kansas, EDHEC, Oklahoma State University, and Texas A&M University.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243–276.

Baker, Malcolm, Lubomir Litov, Jessica A. Watcher, and Jeffrey Wurgler, 2010, Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements, *Journal of Financial and Quantitative Analysis* 45, 1111–1131.

Bamber, Linda S., Orie E. Barron, and Dougles E. Stevens, 2011, Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and directions for future research, *Contemporary Accounting Research* 28, 431–471.

Banerjee, Snehal, and Ilan Kremer, 2010, Disagreement and learning: Dynamic patterns of trade, *Journal of Finance* 65, 1269–1302.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2007, Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490–517.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Berkman, Henk, Valentin Dimitrov, Prem C. Jain, Paul D. Koch, and Sheri Tice, 2009, Sell on the news: Differences of opinion, short sales constraints, and returns around earnings announcements, *Journal of Financial Economics* 92, 376–399.

Boehme, Rodney D., Bartley R. Danielsen, and Sorin M. Sorescu, 2006, Short sale constraints, differences of opinion, and overvaluation, *Journal of Financial and Quantitative Analysis* 41, 455–487.

Boehmer, Ekkehart, Charles M. Jones, and Xioyan Zhang, 2008, Which shorts are informed? *Journal of Finance* 63, 491–527.

Boehmer, Ekkehart, and Eric Kelley, 2009, Institutional investors and the informational efficiency of prices, *Review of Financial Studies* 22, 3563–3594.

Brav, Alon, and J. B. Heaton, 2002, Competing theories of financial anomalies, *Review of Financial Studies*, 15, 575–606.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345–373.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441–464.

Campbell, John Y., 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157–179.

Campbell, John Y., Jen Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Campbell, John Y., Tarun Ramadorai, and Allie Schwartz, 2009, Caught on tape: Institutional trading, stock returns, and earnings announcements, *Journal of Financial Economics* 92, 66–91.

Chae, Joon, 2005, Trading volume, information asymmetry and timing information, *Journal of Finance* 60, 413–442.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681–1713.

Chen, Honghui, Gregory Noronha, and Vijay Singal, 2004, The price response to S&P 500 index additions and deletions: Evidence of asymmetry and a new explanation, *Journal of Finance* 59, 1901–1929.

Chen, Joseph, Samuel G. Hanson, Harrison Hong, and Jeremy C. Stein, 2008, Do hedge funds profit from mutual-fund distress? Working paper, NBER.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.

Chordia, Tarun, and Avanidhar Subrahmanyam, 2004, Order imbalance and individual stock returns: Theory and evidence, *Journal of Financial Economics* 72, 485–518.

Chordia, Tarun, Avanidhar Subrahmanyam, and V. Ravi Anshuman, 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3–32.

Christophe, Stephen E., Michael G. Ferri, and James J. Angel, 2004, Short-selling prior to earnings announcements, *Journal of Finance* 59, 1845–1875.

D'Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271–306.

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277–311.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance* 47, 577–604.

Fama, Eugene F., and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth French, 2002, Testing trade-off and pecking order predictions about dividends and debt, *Review of Financial Studies* 15, 1–33.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 71, 607–636.

Foster, George, Chris Olsen, and Terry Shevlin, 1984, Earnings releases, anomalies, and the behavior of security returns, *The Accounting Review* 59, 574–603.

Frazzini, Andrea, and Owen Lamont, 2006, The earnings announcement premium and trading volume, NBER Working paper 13090.

Gallmeyer, Michael, Burton Hollifield, and Duane Seppi, 2009, Demand discovery and asset pricing, Working paper, University of Virginia and Carnegie Mellon University.

Gao, George P., and Qingzhong Ma, 2012, The sound of silence: What do we know when insiders do not trade? Working paper, Cornell University.

Garfinkel, Jon A., and Jonathan Sokobin, 2006, Volume, opinion divergence, and returns: A study of post-earnings announcement drift, *Journal of Accounting Research* 44, 85–112.

Geczy, Christopher C., David K. Musto, and Adam Reed, 2002, Stocks are special too: An analysis of the equity lending market, *Journal of Financial Economics* 66, 241–269.

Gervais, Simon, Ron Kaniel, and Dan H. Mingelgrin, 2001, The high-volume return premium, *Journal of Finance* 56, 877–919.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313–351.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Johnson, Travis L., and Eric C. So, 2012, The option to stock volume ratio and future returns, *Journal of Financial Economics* 106, 262–286.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman, 2012, Individual investor trading and return patterns around earnings announcements, *Journal of Finance* 67, 639–680.

Kaniel, Ron, Arzu Ozoguz, and Laura Starks, 2012, The high volume premium: Cross country evidence, *Journal of Financial Economics* 103, 255–279.

Kothari, S. P., Jonathan Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics* 79, 537–568.

Lakonishok, Josef, and Inmoo Lee, 2001, Are insider trades informative? *Review of Financial Studies* 14, 79–111.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.

Lerman, Alina, Joshua Livnat, and Richard R. Mendenhall, 2008, The high-volume return premium and post-earnings announcement drift, Working paper, New York University.

Lin, Hsiou-wei, and Maureen F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101–127.

Livnat, Joshuat, and Richard R. Mendenhall, 2006, Comparing the post-earnings-announcement drift for surprises calculated from analyst and time series forecasts, *Journal of Accounting Research* 44, 177–205.

Marin, Jose M., and Jacques Olivier, 2008, The dog that did not bark: Insider trading and crashes, *Journal of Finance* 63, 2429–2476.

Mayshar, Joram, 1983, On divergence of opinion and imperfections in capital markets, *American Economic Review* 73, 114–128.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483–510.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151–1168.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708

O'Brien, Patricia C., Maureen F. McNichols, and Hsiou-wei Lin, 2005, Analyst impartiality and investment banking relationships, *Journal of Accounting Research* 43, 623–650.

Reed, Adam V., 2007, Costly short-selling and stock price adjustment to earnings announcements, Working paper, The University of North Carolina at Chapel Hill.

Sarkar, Asani, and Robert A. Schwartz, 2009, Market sidedness: Insights into motives for trade initiation, *Journal of Finance* 64, 375–423.

Schneider, Jan, 2009, A rational expectations equilibrium with informative trading volume, *The Journal of Finance* 64, 2783–2805.

Seyhun, Nejat H., 1986, Insiders' profits, costs of trading, and market efficiency, *Journal of Financial Economics* 16, 189–212.

Seyhun, Nejat H., 1998, *Investment Intelligence from Insider Trading* (MIT Press, Cambridge, MA).

Sorescu, Sorin M., 2000, The effect of options on stock prices: 1973–1995, *Journal of Finance* 55, 487–514.

Varian, Hal R., 1985, Divergence of opinion in complete markets: A note, *Journal of Finance* 40, 309–317.

Vega, Clara, 2006, Stock price reaction to public and private information, *Journal of Financial Economics* 82, 103–133.

Wang, Jiang, 1994, A model of competitive stock trading volume, *Journal of Political Economy* 102, 127–168.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.