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SKEWNESS AND THE ASYMMETRY IN EARNINGS ANNOUNCEMENT RETURNS

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Abstract

Much of traditional asset pricing theory rests on the assumption of normality in the distribution of stock returns. A growing body of research suggests that skewness in the return distributions can affect asset prices. In this article we attempt to empirically identify factors that influence return skewness. Consistent with the theoretical literature, we find that prices during the postearnings announcement period are more convex for firms that have tighter short-sale constraints and for firms that experience greater disagreement among investors. Perhaps more important, we also find that price convexity is a key determinant in the skewness of stocks.

JEL Classification: G10, G12, G14

I. Introduction

Much of traditional asset pricing theory rests on the assumption of normality in the distribution of stock returns. However, prior research documents negative skewness in market returns (e.g., Black 1976; Christie 1982; Schwert 1989; Bekaert and Wu 2000) and positive skewness in individual stock returns (Harvey and Siddique 1999, 2000; Chen, Hong, and Stein 2001). The presence of skewness might introduce bias into some of the asset pricing models that are used by both academics and practitioners. Furthermore, more recent research suggests that investors might have preferences for skewness, that will affect asset prices more generally. For instance, Barberis and Huang (2008) use prospect theory to show that some investors will overweight the tails in return distributions, thus leading to skewness preferences. Barberis and Huang show that these preferences, if strong enough, can lead to stock price premiums and subsequent underperformance. Empirical evidence seems to confirm these theoretical predictions as

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stocks with the most positive skewness significantly underperform stocks with the most negative skewness (Mitton and Vorkink 2007; Kumar 2009; Boyer, Mitton, and Vorkink 2010; Kumar, Page, and Spalt 2011). Given the evidence that indicates that skewness affects asset prices, an important extension to this growing body of research might be to identify factors that lead to skewness in the distribution of stock returns. The main objective of this study is to provide these tests.

Underlying most theories of skewness are the assumptions of short-sale constraints and heterogeneous expectations (Hong and Stein 2003; Diamond and Verrecchia 1987). Xu (2007) nicely develops the theoretical relation between both short-sale constraints and heterogeneous beliefs and skewness. He argues that in the presence of constraints and heterogeneity, stock prices react more to good news than to bad news, which will result in convex prices across the news signal and lead to more positive return skewness. In some initial tests, Xu shows that, in general, postearnings announcement returns are indeed convex and that both short-sale constraints and heterogeneous beliefs directly affect skewness. In this article, we extend these empirical results by examining several other predictions in Xu that have not been tested. In particular, we test whether the price convexity in postannouncement returns is directly related to both short-sale constraints and heterogeneous beliefs. Furthermore, we test whether price convexity affects the skewness in stock return distributions.

Consistent with the predictions in Xu (2007), we first find that price responses following earnings announcements are more convex for firms that have tighter short-sale constraints. These results hold in both univariate sorts and multivariate tests, and suggest that stocks prices react more to good news than to bad news. Second, we find weak evidence that postannouncement price convexity is also driven by stocks with greater heterogeneity when approximated with return volatility. We do not find a significant link between price convexity and share turnover, which has also been shown to proxy for heterogeneous beliefs (Xu 2007; Berkman et al. 2009). Therefore, the evidence between price convexity and heterogeneity is weak at best. Third, we examine whether price convexity is positively related to skewness. Results show that the convexity in postannouncement returns is a key determinant in contemporaneous skewness for our sample of NYSE stocks. We are not, however, able to draw similar conclusions when focusing on our sample of NASDAQ-listed stocks. To the extent that both short-sale constraints and heterogeneous beliefs can affect the skewness of returns (as in Xu 2007), our empirical tests show that the relation between constraints and skewness can be explained by constraint-induced price convexity. After estimating this convexity, we show that NYSE-listed stocks with the greatest convexity generally have the highest return skewness. Combined with our earlier findings, these results seem to indicate that although the lack of short selling and greater disagreement among investors can lead to higher skewness, the results from our tests suggest that the mechanism through which this occurs is through the convexity associated with postannouncement returns. Given the growing body of research that discusses potential biases in asset prices caused by skewness, our findings contribute to this literature by identifying how stock return distributions might become more skewed.

II. Hypotheses Development

In this section, we review the relevant literature and develop our hypotheses. As mentioned earlier, our tests are motivated by theoretical predictions in Xu (2007). His model suggests that binding short-sale constraints and heterogeneous beliefs about the precision of public signals allow bullish investors to crowd out bearish investors who are unable to short their stock. This crowding out leads to the convexity in price responses across the magnitude of the signal because, without short selling, the market overreacts to positive news and underreacts to negative news. Although Xu's total sample results are consistent with the prediction of his model, his tests do not condition on the necessary conditions of his model. Our first tests, therefore, examine the convex price response to earnings announcements while conditioning on proxies for the tightness of short-sale constraints or the degree of investor disagreement. We formally state our first hypothesis below:

H1: *Price convexity in the response to earnings announcements is more likely to be observed in stocks with the tightest short-sale constraints and in stocks with the most disagreement among investors.*

Our second set of tests examine conflicting predictions in Xu (2007) and Diamond and Verrecchia (1987).[1] By definition, the convex price function depicted in Xu is steeper for positive signals compared to negative signals. Therefore, for signals of equal size, a positive signal increases the price more than a negative signal decreases it. Based on this insight, Xu argues that contemporaneous skewness must increase in the signal if price responses to earnings announcements are convex. Using a rational expectations framework, Diamond and Verrecchia argue, by contrast, that short-sale constraints delay the incorporation of preannouncement bad news into stock prices. Thus, when stocks respond to negative earnings surprises, the response reflects the effects of both the past suppressed and the newly revealed negative information. If this argument holds, the absolute value of returns for negative surprises should be larger than the absolute value of returns for positive surprises, resulting in negative skewness. We consider returns in the immediate postannouncement periods and examine the potential relation between the convexity of announcement-period returns and the ensuing skewness. To the extent that the theory in Xu is correct, the second hypothesis we test can be stated as follows:

H2: *Skewness relates positively to the degree of convexity in the stock price response to earnings announcements.*

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[1] For reasons unrelated to short-sale constraints, opposite predictions also arise from managerial incentives to release good news differently from bad news. For example, Chen, Hong, and Stein (2001) argue that management's tendency to release good news all at once and bad news gradually over time induces positive skewness. Ekholm and Pasternack (2005) argue, by contrast, that managers' tendency to announce all good news and extreme bad news, but not moderately bad news, leads to negative skewness. Though earnings announcements are not discretionary and the numbers may seem objective, Engelberg (2008) and Demers and Vega (2010) show that the discretionary qualitative information contained in earnings announcements can also influence or predict short-term returns. Thus, even for discretionary announcements, managers can shape the message of their disclosures.

III. Data Description

Our sample consists of NYSE- and NASDAQ-listed stocks for a 32-year period (1980–2012). We obtain our data from several sources. From the Center for Research in Security Prices (CRSP), we get monthly stock prices, shares outstanding, and volume, which we aggregate to the quarterly level. We also use daily CRSP returns to calculate quarterly return volatility and skewness.

Using daily returns from CRSP, we estimate skewness as the scaled third moment in the return distribution. The equation for our skewness calculations is given below:

$$Skew = \frac{t}{(t-1)(t-2)}\left(\frac{\sum_{j=1}^{t}(r_j-\bar{r})^3}{\hat{\sigma}^3}\right), \qquad (1)$$

where r_t is the CRSP raw return for a particular stock on day t, $\bar{r}$ is the mean return, and $\hat{\sigma}$ is the estimate for the standard deviation of returns for a particular stock during a particular quarter.

From Compustat, we obtain the earnings announcement dates and the reported earnings. Following Chan et al. (1996), Chordia and Shivakumar (2002), and Sadka (2006) we calculate the standardized unexpected earnings (*SUE*) as our measure of earnings surprise, as given by:

$$SUE_{i,t} = \frac{E_{i,q} - E_{i,q-4} - c_{i,t}}{\sigma_{i,t}}, \qquad (2)$$

where $E_{i,q}$ is the most recent quarterly earnings for stock i, $E_{i,q-4}$ is the four-quarter lagged earnings, and $c_{i,t}$ ($\sigma_{i,t}$) is the average (standard deviation) of $E_{i,q} - E_{i,q-4}$ for the previous eight quarters.[2]

From Thomson's Spectrum database, we use 13f filings to calculate institutional ownership (the proportion of shares outstanding held by institutions) and ownership

[2] Xu (2007) uses the percentage difference between actual earnings and analyst earnings. Using this alternative measure of earnings surprise produces qualitatively similar results. We choose to report the results using *SUE* because we are only able to obtain analyst forecasts using IBES, which Ljundqvist, Malloy, and Marston (2009) show are inaccurate. Furthermore, much of the sample is lost when requiring stocks to have analyst coverage. Requiring stocks that have analyst coverage might also violate the random sampling assumption. For instance, stocks with no analyst coverage are generally smaller stocks that will likely face tighter short-sale constraints. Given that our hypotheses rely heavily on the presence of short-sale constraints, we choose to retain the stocks without analyst coverage.

breadth (the number of institutional shareholders). We also obtain monthly short interest data directly from Compustat. After merging these data together, we have 6,148 stocks and 172,968 stock-quarter observations in our sample.[3]

Panels A and B of Table 1 report descriptive statistics for NYSE-listed and NASDAQ-listed stocks, respectively. Panel C reports differences between means in Panels A and B, and *t*-statistics from tests of the null hypothesis that the means are equal. The average NYSE stock has a market capitalization (*Size*) of approximately $14.8 billion; institutional ownership (*InstOwn*) of .563; 209.86 institutional shareholders (*Breadth*); turnover, or the ratio of trading volume to shares outstanding (*Turn*), of 1.3357%; return volatility (*Rvolt*) of 2.28%; relative short interest, or the ratio of short interest to shares outstanding (*RSI*), of nearly 3%; skewness (*Skew*) of .1925; and *SUE* of −.6728. The average NASDAQ stock has *Size* of $2.27 billion, *InstOwn* of .4853, *Breadth* of 96.03, *Turn* of 1.4681, *Rvolt* of 3.27%, *RSI* of 3.81%, *Skew* of .3628, and *SUE* of −1.1011.

Panel C of Table 1 shows that relative to NASDAQ stocks, the average NYSE stock has more market cap (difference = 12.5554, *t*-statistic = 26.32), higher institutional ownership (difference =.0776, *t*-statistic = 51.82), more ownership breadth (difference = 113.93, *t*-statistic = 142.43), less turnover (difference = −.1324, *t*-statistic = −11.43), lower return volatility (difference = −.0099, *t*-statistic = −98.33), less relative short interest (difference = −.0086, *t*-statistic = −28.64), lower skewness (difference = −.1703, *t*-statistic = −30.15), and less negative *SUE* (difference =.4283, *t*-statistic = 8.07). These reliable differences suggest the need to test our hypotheses separately for NYSE and NASDAQ stocks.

IV. Results

In this section, we test both of our hypotheses. First, we test whether the convex price response to earnings announcements is driven by stocks that are most likely constrained and most likely to have high levels of investor disagreement. Second, we determine whether skewness relates positively to price convexity.

Convex Price Response to Earnings Announcements

Table 2 reports mean cumulative abnormal returns (CARs) for various postannouncement periods extending from two days (CAR(0,1)) to six days (CAR(0,5)). Abnormal returns are difference between CRSP raw returns and the value-weighted CRSP index. CARs are reported for the entire sample (column [1]) and across SUE quartiles 1 through 4 (Q1 through Q4), where Q1 and Q4 contain firms with the least and most favorable earnings surprises, respectively. Panels A and B again report results for NYSE-listed and NASDAQ-listed stocks, respectively. Results in column [1] indicate that CARs for all SUE quartiles combined are positive for the NYSE sample and the NASDAQ sample.

[3] Some stock-quarter observations were excluded because fewer than 40 daily observations were available to calculate skewness.

TABLE 1. Summary Statistics.

	Size	*InstOwn*	*Breadth*	*Turn*	*Rvolt*	*RSI*	*Skew*	*SUE*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A. NYSE-Listed Stocks								
Mean	14.8251	0.5629	209.86	1.3357	0.0228	0.0295	0.1925	−0.6728
Std dev	156.3030	0.2786	211.59	2.3503	0.0144	0.0549	0.9566	8.8588
25th perc	0.5520	0.3589	77.00	0.4384	0.0144	0.0034	−0.2027	−1.7945
Median	1.7753	0.5954	148.00	0.8349	0.0193	0.0124	0.1689	0.0188
75th perc	5.9157	0.7902	269.00	1.6230	0.0268	0.0340	0.5652	1.7354
Panel B. NASDAQ-Listed Stocks								
Mean	2.2697	0.4853	96.03	1.4681	0.0327	0.0381	0.3628	−1.1011
Std dev	19.9920	0.3104	120.80	2.2945	0.0226	0.0631	1.2151	11.4706
25th perc	0.0715	0.2017	20.00	0.3421	0.0196	0.0019	−0.1502	−3.5639
Median	0.2607	0.4786	63.00	0.8526	0.0276	0.0178	0.2700	−0.0068
75th perc	0.8999	0.7598	126.00	1.8762	0.0392	0.0485	0.7742	2.9123
Panel C. Mean Differences (Panel A – Panel B)								
Difference	12.5554***	0.0776***	113.93***	−0.1324***	−0.0099***	−0.0086***	−0.1703***	0.4283***
p-value	(26.32)	(51.82)	(142.43)	(−11.43)	(−98.33)	(−28.64)	(−30.15)	(8.07)

Note: The table reports statistics that describe the sample of stocks used in the analysis. Panel A reports the results for NYSE-listed stocks and Panel B reports the results for NASDAQ-listed stocks. Panel C reports the difference in the means between Panels A and B. *Size* is the market capitalization in $ billions, *InstOwn* is the number of shares held by institutions scaled by shares outstanding. *Breadth* is the number of institutional shareholders. *Turn* is the number shares traded during a quarter divided by shares outstanding in percentage from months $t-6$ to $t-1$, where t is the earnings announcement month. *Rvolt* is the return volatility of standard deviation of daily returns during the six months preceding the earnings announcement. *RSI* is the relative short interest obtained from Compustat. *Skew* is the skewness of daily returns during each year. *SUE* is the standardized unexpected earnings following Sadka (2006), among others. The *t*-statistics are reported in parentheses.
***Significant at the 1% level.

TABLE 2. Cumulative Abnormal Returns and Standardized Unexpected Earnings.

	All Stocks	SUE Quartile 1 (Low)	SUE Quartile 2	SUE Quartile 3	SUE Quartile 4 (High)	Difference [Q4−Q5]
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A. Returns around Earnings Announcements: NYSE-Listed Stocks						
CAR(0,1)	0.0021	−0.0048	−0.0003	0.0048	0.0088	0.0136*** (21.05)
CAR(0,2)	0.0024	−0.0051	−0.0003	0.0053	0.0095	0.0146*** (20.25)
CAR(0,3)	0.0025	−0.0050	−0.0004	0.0057	0.0095	0.0145*** (18.92)
CAR(0,4)	0.0026	−0.0053	−0.0006	0.0063	0.0099	0.0152*** (18.70)
CAR(0,5)	0.0030	−0.0049	−0.0004	0.0069	0.0104	0.0153*** (18.24)
Panel B. Returns around Earnings Announcements: NASDAQ-Listed Stocks						
CAR(0,1)	0.0012	−0.0151	−0.0051	0.0078	0.0170	0.0321*** (40.56)
CAR(0,2)	0.0005	−0.0165	−0.0065	0.0077	0.0173	0.0338*** (39.42)
CAR(0,3)	0.0002	−0.0170	−0.0075	0.0079	0.0173	0.0343*** (37.89)
CAR(0,4)	0.0004	−0.0171	−0.0073	0.0081	0.0180	0.0351*** (37.05)
CAR(0,5)	0.0006	−0.0171	−0.0074	0.0083	0.0185	0.0356*** (36.25)

Note: The table examines cumulative abnormal returns (CARs) for various time windows around earnings announcements. Abnormal returns are stock returns in excess of the CRSP value-weighted market return. Following Sadka (2006) we calculate the standardized unexpected earnings (*SUE*) using the following equation:

$$SUE_{i,t} = \frac{E_{i,q} - E_{i,q-4} - c_{i,t}}{\sigma_{i,t}},$$

where $E_{i,q}$ is the most recent quarterly earnings announced for stock i and $E_{i,q-4}$ is earnings for the prior four quarters. $C_{i,t}$ and $\sigma_{i,t}$ are the average and standard deviation of ($E_{i,q}$ – $E_{i,q-4}$), respectively. We calculate abnormal returns around earnings announcements and take the difference between returns in highest SUE quartile (greatest positive earnings surprise) and returns in the smallest SUE quartile (most negative earnings surprise). The *t*-statistics testing whether the difference is statistically significant are reported in parentheses.

***Significant at the 1% level.

Furthermore, in both panels, we see that CARs increase monotonically across SUE quartiles (columns [2] through [5]) and that mean differences between extreme portfolios are positive and significant (column [6]). These results are expected if SUE conveys value-relevant information to the market.

Figure I portrays the returns in Table 2 graphically for our two samples. Differences in the patterns of postannouncement returns seem to confirm the results in Xu (2007) as CARs exhibit the expected convexity from Q1 to Q3. We do not find that the convex price response continues from Q3 to Q4. These findings are remarkably similar to the findings in Xu. Furthermore, the results are robust to the different postannouncement time windows. Although this relation is largely unexplained in Xu, it is possible that when controlling for stock-specific factors, we will observe the expected convexity in our multivariate tests. We test for this explanation below.

Although our results in Table 2 and Figure I provide some consistency with the findings from Xu (2007), before moving on to our multivariate tests we next condition the

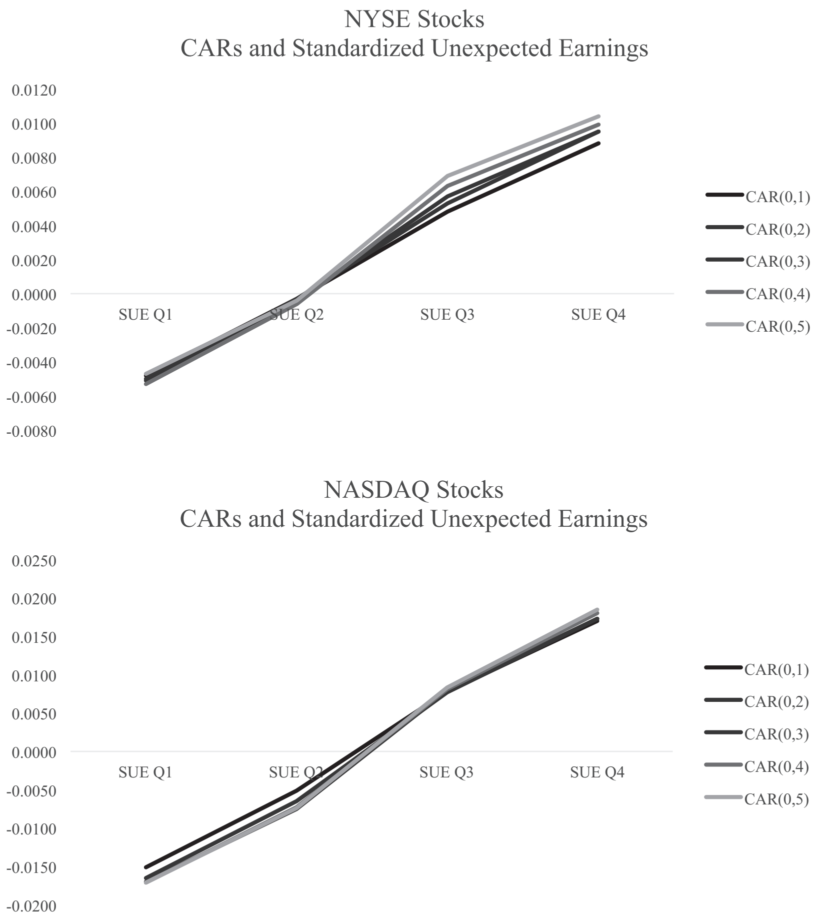

Figure I. Cumulative Abnormal Returns (CARs) during Different Event Windows Surrounding Earnings Announcements across Standardized Unexpected Earnings Quartiles. The top panel shows the results for NYSE-listed stocks and the bottom panel shows the results for NASDAQ-listed stocks.

graphs in Figure I on factors that give rise to convexity in Xu's model. Figures II through V remediate that problem by comparing price responses for firms with varying short-sale constraints and for firms with high versus low dispersion of investor opinion. Figures II and III depict results while conditioning on Xu's proxies for short-sale constraints (including relative short interest) and Figures IV and V present the graphs

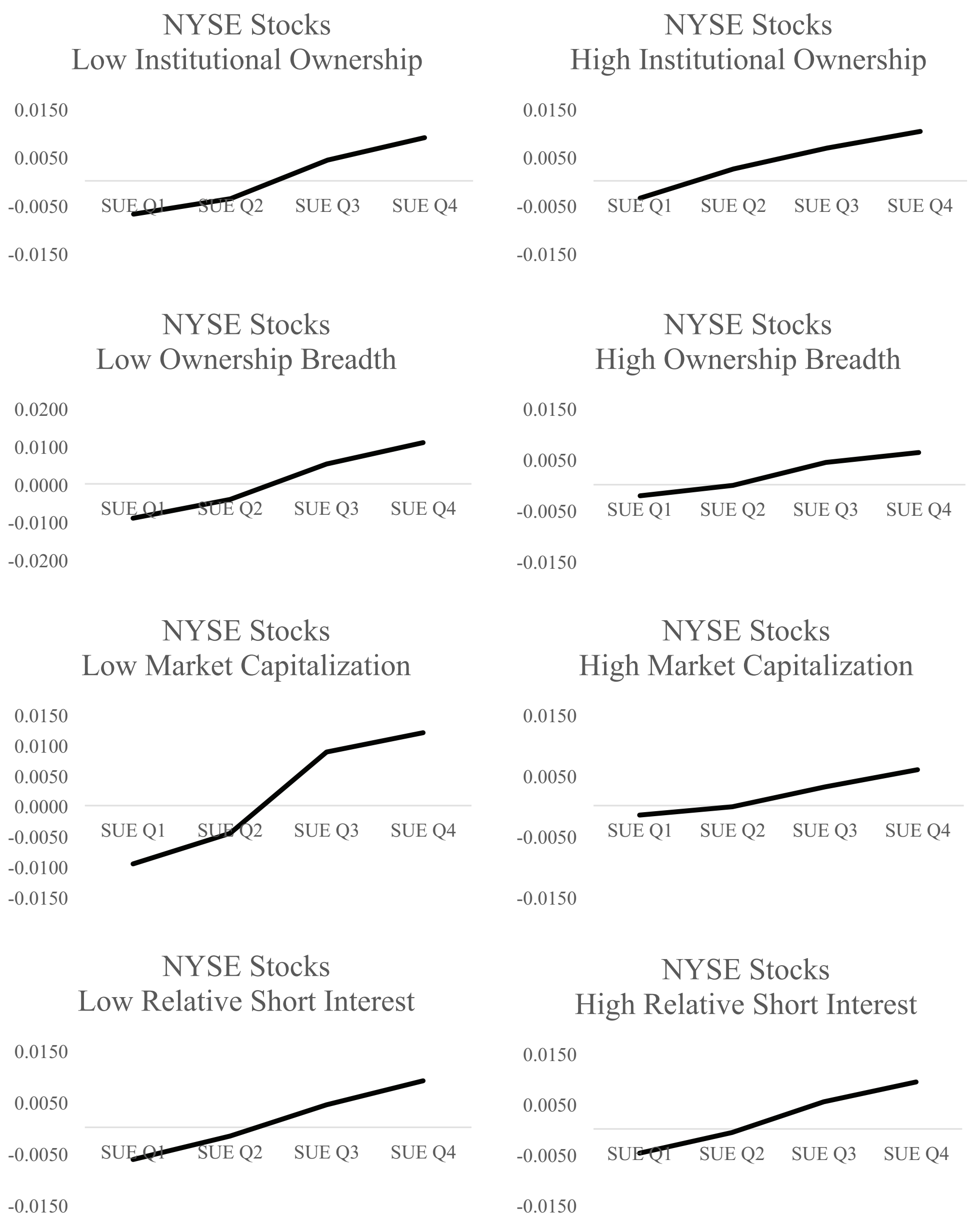

Figure II. Cumulative Abnormal Return from Day 0 to Day 1 (CAR(0,1)) across Standardized Unexpected Earnings (SUE) Quartiles for NYSE-Listed Stocks that Are Constrained (Left Panels) and Stocks that Are Not Constrained (Right Panels).

while conditioning on Xu's proxies for heterogeneous beliefs. Furthermore, Figures II and IV show the results for the NYSE sample and Figures III and V present the results for the NASDAQ sample.

We note that the inverse proxies for short-sale constraints include institutional ownership, ownership breadth, and market cap as in Xu (2007), Arnold et al. (2005), Asquith, Pathak, and Ritter (2005), Nagel (2005), and Berkman et al. (2009). We also include short interest as an inverse proxy for short-sale constraints. D'Avolio (2002) argues that the equity loan supply relates directly to the level of institutional holdings

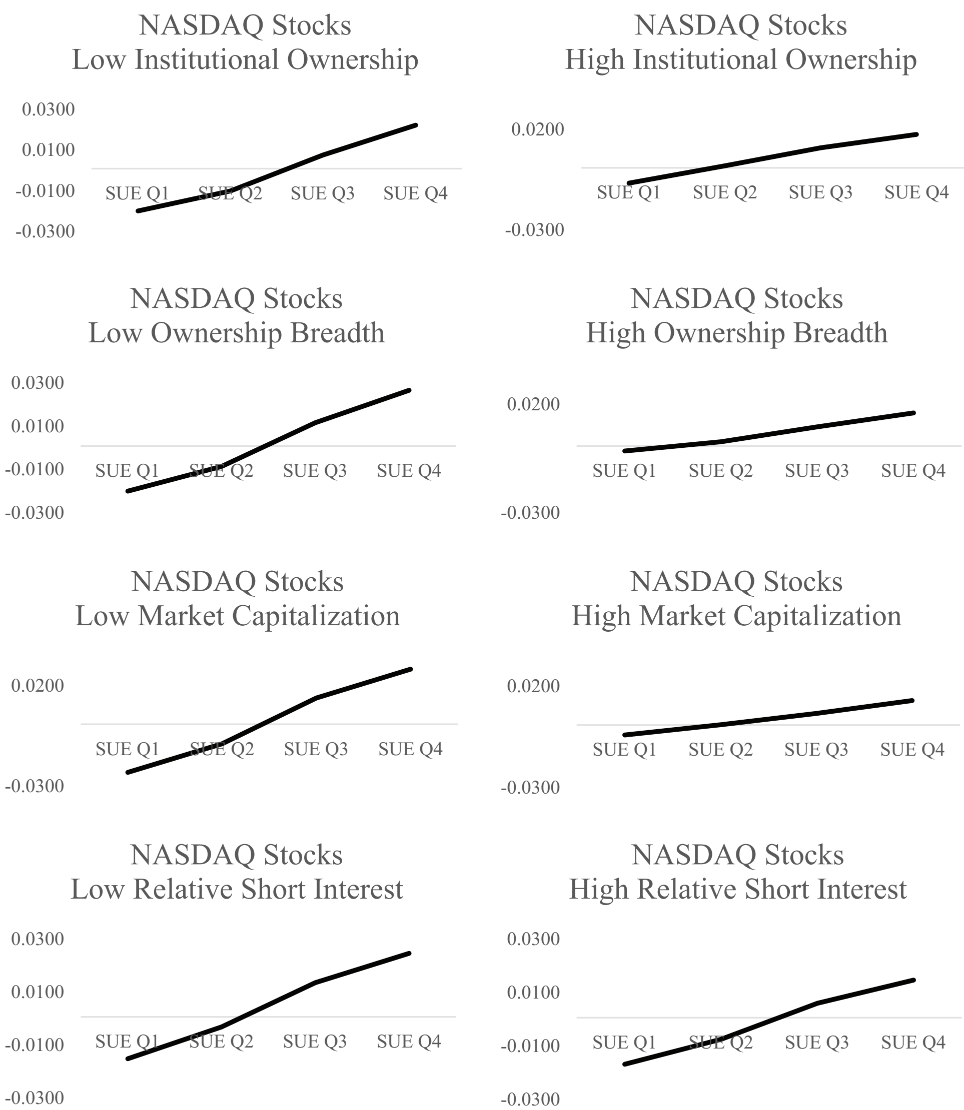

Figure III. Cumulative Abnormal Return from Day 0 to Day 1 (CAR(0,1)) across Standardized Unexpected Earnings (SUE) Quartiles for NASDAQ-Listed Stocks that Are Constrained (Left Panels) and Stocks that Are Not Constrained (Right Panels).

Figure IV. Cumulative Abnormal Return from Day 0 to Day 1 (CAR(0,1)) across Standardized Unexpected Earnings (SUE) Quartiles for NYSE-Listed Stocks with Low Heterogeneity (Left Panels) and Stocks with High Heterogeneity (Right Panels).

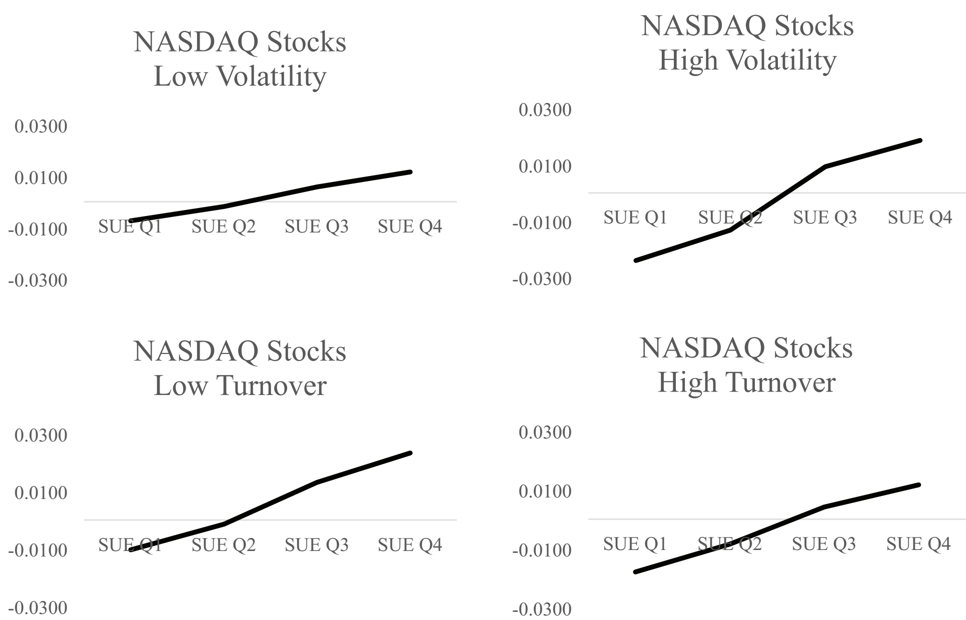

Figure V. Cumulative Abnormal Return from Day 0 to Day 1 (CAR(0,1)) across Standardized Unexpected Earnings (SUE) Quartiles for NASDAQ-Listed Stocks with Low Heterogeneity (Left Panels) and Stocks with High Heterogeneity (Right Panels).

because institutions are the primary lenders of shares to short sellers, and stocks with lower institutional holdings have lower equity loan supply and are more likely to be constrained. Along with Xu (2007), Chen, Hong, and Stein (2002) argue that ownership breadth is an inverse proxy for short-sale constraints. Arnold et al. suggest that institutions generally hold larger cap stocks, thus explaining the positive relation between the equity loan supply and market cap found in D'Avolio. Finally, Chen, Hong, and Stein also argue that short interest is an inverse proxy for short-sale constraints and that firms in which short interest is high have lower costs of short selling and vice versa.

Figure II presents CARs(0,1) across SUE quartiles for NYSE-listed stocks in the lowest and highest quartiles of the inverse proxies discussed in the previous paragraph. In each case, results in the left panels are for stocks most likely to be constrained and results in the right panels are for stocks least likely to be constrained. According to Xu (2007), convexity should be more pronounced for stocks in our constrained subsamples than in our unconstrained subsamples. Results are generally consistent with that prediction for institutional ownership, ownership breadth, and market cap as the convexity appears to be more pronounced in the left panel than in the right panel. For short interest, the CAR pattern in the left panel does not appear different from the right panel. Again, we note that convexity in the left panels seems to only exist in Q1 through Q3. Figure III shows the results for NASDAQ-listed stocks. Again, the results are similar to those in Figure II as the convex price response to earnings announcements seems to be stronger in the left panels than in the right panels.

Xu (2007) also argues that investor disagreement or heterogeneous beliefs lead to price convexity. Following Berkman et al. (2009) and Xu, we use return volatility and turnover as proxies for disagreement in investors' opinions. We estimate both measures during the six months preceding the earnings announcement. According to Xu, convexity should be greater for stocks with high volatility and/or turnover. Figures IV and V examine that prediction for NYSE- and NASDAQ-listed stocks, respectively. After sorting stocks into quartiles based on these two proxies for disagreement, we examine price convexity firms in the lowest (left panel) and highest (right panel) volatility and turnover quartiles. To the extent that Xu's model and our hypothesis hold, we expect convexity to be more pronounced in the right panels than in the left panels.

Figure IV shows the results for the NYSE-listed stocks and Figure V presents the results for the NASDAQ-listed stocks. In Figure IV, we find that the volatility plots are reasonably consistent with Xu's (2007) predictions. However, the turnover sorts are not as strong. These results are similar for NASDAQ stocks in Figure V. It is possible that turnover does not present a meaningful proxy for heterogeneous beliefs and instead is a proxy for liquidity. To the extent that this is true, it is not surprising that convexity is slightly more pronounced in stocks with lower turnover. These stocks might face liquidity constraints, which make it difficult for the price response to earnings announcements to be linear across the earnings signal. This explanation is outside of the scope of this article, but tests of liquidity constraints and price convexity might be a fruitful avenue for future research. Although the combined results provide some graphical support for our first hypothesis, we recognize the need to control for convexity in multivariate setting. We conduct these tests next.

We begin by estimating the following equation:

$$CAR(0,1)_{i,t} = \alpha + \theta_1 SUE_{i,t} + \theta_2 SUE^2_{i,t} + \beta_1 \ln(Size_{i,t}) + \beta_2 \ln(Price_{i,t}) + \beta_3 Turn_{i,t-6,t-1} + \beta_4 Rvolt_{i,t-6,t-1} + \eta_{i,t}. \quad (3)$$

The dependent variable is the cumulative abnormal return from day 0 to day 1, where day 0 is the earnings announcement date (*CAR*(0,1)). The independent variables include *SUE* and the squared term SUE^2 associated with the earnings announcement. If postannouncement returns are a convex function of the earnings signal, both coefficients on the independent variables are expected to be positive. We also include as control variables the natural log of market capitalization (ln(*Size*)), the natural log of the share price (ln(*Price*)), share turnover during the six months preceding earnings announcement (*Turn*), and return volatility during the six months preceding the earnings announcement (*Volt*). In response to a Hausman test, we include year fixed effects.

Results from estimating equation (3) are reported in Table 3. We estimate the equation for NYSE-listed stocks (columns [1] and [2]) and NASDAQ-listed stocks (columns [3] and [4]). We report *t*-statistics in parentheses that are obtained from standard errors that account for two-dimensional clustering. With respect to the control variables, we find that two-day CARs are negatively related to market capitalization and turnover, and positively related to share prices and return volatility. These results are robust in columns [2] and [4]. In columns [1] and [3], we include only our independent variables of interest, *SUE* and SUE^2. Column [1] shows that for NYSE-listed stocks, both coefficients are positive and significant (estimates = .0561, .0005; *t*-statistics = 19.91, 3.35). These results suggest that postannouncement CARs are convex across earnings surprises. When we include the control variables in column [2], we still find that the coefficients on *SUE* and SUE^2 are positive and reliably different from zero (estimates = .0566, .0006; *t*-statistics = 20.26, 4.19). Columns [3] and [4] show the results for NASDAQ-listed stocks. Again, we find that the coefficients on *SUE* and SUE^2 are positive and significant and, if anything, greater in magnitude than those in the first two columns. These results suggest that after controlling for other stock characteristics that may influence postannouncement CARs, returns are indeed convex across SUE. Perhaps the nonconvexity we observed across the top two quartiles of SUE (in the top panel of Figure I) is simply a function of noncontinuous sorts. In any case, the findings in Table 3 support theory in Xu (2007) that posits that prices are convex across earnings signals.[4]

[4] In a series of robustness tests, we estimate equation (3) for various subperiods used in the analysis. In particular, we test whether the main results in Table 3 hold during the 1980s, 1990s, and 2000s. The results from these unreported tests show that, in general, convexity exists throughout our sample period. However, we find the strongest results during the most recent period (2000s). We also note that we are able to find only weak evidence of convexity during the 1990s. The coefficients for SUE^2 for both NYSE- and NASDAQ-listed stocks, while positive, are not reliably different from zero. Perhaps the lack of significance is due to the lack of power in our tests. Or, perhaps the 1990s were a unique period. Battalio and Schultz (2006) argue that during the NASDAQ bubble period (during the latter part of the 1990s), short-sale constraints were not binding. The lack of short-sale constraints during this period might also explain the lack of significance during the 1990s.

TABLE 3. Convexity Regressions.

	NYSE-Listed Stocks		NASDAQ-Listed Stocks	
	[1]	[2]	[3]	[4]
Intercept	0.4525**	−1.0378**	0.4869**	1.1042***
SUE	0.0561***	0.0566***	0.1039***	0.1030***
	(19.91)	(20.26)	(35.33)	(35.10)
SUE^2	0.0005***	0.0006***	0.0008***	0.0009***
	(3.35)	(4.19)	(5.72)	(6.33)
ln(*Size*)		−0.0425***		−0.1182***
		(−3.06)		(−6.53)
ln(*Price*)		0.4445***		0.6461***
		(8.01)		(14.61)
Turn		−0.0522**		−0.1757***
		(−1.96)		(−9.01)
Volt		0.3620***		0.1256***
		(6.21)		(3.79)
Adjusted R^2	0.0076	0.0120	0.0154	0.0197
Year fixed effects	Yes	Yes	Yes	Yes
Robust std errors	Yes	Yes	Yes	Yes

Note: The table reports the cross-sectional regression results from estimating the following regression:

$$CAR(0,1)_{i,t} = \alpha + \theta_1\, SUE_{i,t} + \theta_2\, SUE^2_{i,t} + \beta_1 \ln(Size_{i,t}) + \beta_2 \ln(Price_{i,t}) + \beta_3 Turn_{i,t-6,t-1} + \beta_4 Rvolt_{i,t-6,t-1} + \eta_{i,t}.$$

The dependent variable is the cumulative abnormal return from day 0 to day 1 (*CAR*(0,1)), where day 0 is the earnings announcement date. The independent variables include the standardized unexpected earnings (*SUE*) and the squared term (SUE^2) associated with the earnings announcement. If postannouncement returns are a convex function of the earnings signal, then both coefficients on the independent variables are expected to be positive. We also include as control variables the natural log of market capitalization (ln(*Size*)), natural log of the share price (ln(*Price*)), share turnover during the six months preceding the earnings announcement in month t (*Turn*), and return volatility during the six months preceding the earnings announcement in month t (*Volt*). In response to a Hausman test, we include year fixed effects. We estimate the equation for NYSE-listed stocks (columns [1] and [2]) and NASDAQ-listed stocks (columns [3] and [4]). We report t-statistics that are obtained from standard errors that account for two-dimensional clustering in parentheses.
***Significant at the 1% level.
**Significant at the 5% level.

With the results in Table 3 as our baseline, we next test our hypothesis by estimating equation (3) for subsamples of stocks that reflect constrained stocks or stocks that have greater heterogeneity in investor beliefs. After sorting stocks into quartiles based on our proxies for short-sale constraints, we begin by reporting the results from estimating equation (3) for stocks that are the most and least constrained. As before, we control for year fixed effects and report t-statistics from robust standard errors that account for two-dimensional clustering. Table 4 reports the results. Panel A presents the results for NYSE-listed stocks and Panel B presents the results for NASDAQ-listed stocks. In Panel A, columns [1] and [2] report the results for stocks with the least institutional ownership and the most institutional ownership, respectively. Focusing on the independent variables of interest, we find in column [1] that both *SUE* and SUE^2 produce coefficients that are positive and statistically significant. Furthermore, the coefficients are slightly larger than the corresponding coefficients for the entire NYSE sample in Table 3. Column [2] shows that the coefficient on SUE^2 is not reliably different from zero. A coefficient on SUE^2 that is close to zero suggests that the price response to earnings announcements is linear. These results suggest that, if anything, the convexity we observe in Table 3 is driven by stocks with the least institutional ownership or, as D'Avolio (2002) argues, stocks that are most likely to face short-sale constraints.

In the remainder of the columns of Table 4, we find qualitatively similar results to those in the first two columns. Said differently, stocks that are most likely to face constraints (according to our proxies) typically have positive and significant coefficients on *SUE* and SUE^2, whereas stocks that are least likely to face constraints do not generate significant coefficients for SUE^2. There is a slight exception. In column [3], the coefficient on SUE^2 for the low-ownership-breadth subsample, though positive, is significant only at the .10 level. The robust *t*-statistic is 1.92. We note that at the bottom of the panels, we report the low minus high difference in the coefficient on SUE^2 with a corresponding *t*-statistic (in parentheses). For instance, at the bottom of columns [5] and [6], we find that the difference is .0006 (*t*-statistic = 1.79), suggesting that the coefficient on SUE^2 is significantly larger in column [5] than in column [6]. Whereas the other differences reported at the bottom of Panel A are not significant, in stocks with the lowest short-sale constraint proxies the coefficients on SUE^2 are positive and reliably different from zero. In stocks with the highest proxies, we do not find that the coefficients are different from zero.

Panel B of Table 4 shows the results for NASDAQ-listed stocks. In columns [1] and [2], we find that the coefficients on *SUE* and SUE^2 are positive and significant for both subsets of stocks. However, we note that the coefficients on SUE^2 are markedly larger for stocks that are the most constrained compared to stocks that are the least constrained. At the bottom of the panel, we provide differences with corresponding *t*-statistics. As seen in the bottom row of Panel B, when comparing the magnitude of the coefficients on SUE^2 in columns [1] and [2], a *t*-statistic testing for equality is 2.48, suggesting that the coefficients on SUE^2 is significantly larger in column [1] than in column [2]. Furthermore, the differences are economically meaningful. For instance, the coefficient on SUE^2 is more than twice as large in column [1] than in column [2]. Qualitatively similar results are found when we use ownership breadth and market capitalization as our proxies for short-sale constraints. In column [7], we find that the coefficient on SUE^2 is approximately 43% larger than the corresponding coefficient in column [8]. However, the *t*-statistic testing for equality is only 1.10, suggesting that the coefficients on SUE^2 are not reliably different from zero for stocks with the lowest *RSI* compared to stocks with the highest *RSI*. In every other case, our results support the first part of our first hypothesis that is based on the idea in Xu (2007) that short-sale constraints will crowd out bearish investors during the postannouncement period, which results in more price convexity. Next, we test whether the price convexity in our general tests are driven by stocks with the greatest heterogeneity in investors' beliefs.

Following the intuition of our tests in Table 4, Table 5 presents the results for estimating equation (3) for subsets of stocks that reflect the greatest (and the least) heterogeneity. Again, we proxy for heterogeneity using return volatility and turnover as in Xu (2007). As before, Panel A shows the results for NYSE-listed stocks and Panel B shows the results for NASDAQ-listed stocks.

TABLE 4. Convexity Regressions and Short-Sale Constraints.

	Low *InstOwn*	High *InstOwn*	Low *Breadth*	High *Breadth*	Low *Size*	High *Size*	Low *RSI*	High *RSI*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A. NYSE-Listed Stocks								
Intercept	−0.9680	−2.9060***	−0.8231	0.2163	−0.4395	0.4094	0.3599	−3.3405
	(−1.36)	(−2.75)	(−1.09)	(0.26)	(−0.35)	(0.44)	(0.58)	(−4.03)
SUE	0.0564***	0.0817***	0.0619***	0.0415***	0.0733***	0.0377***	0.0423***	0.0850***
	(11.19)	(11.03)	(11.43)	(8.01)	(11.35)	(7.53)	(11.31)	(10.97)
SUE^2	0.0007***	0.0004	0.0005*	0.0003	0.0010***	0.0004	0.0005***	0.0006
	(2.61)	(1.19)	(1.92)	(1.32)	(2.98)	(1.55)	(2.57)	(1.54)
ln(*Size*)	−0.0225	−0.0157	−0.0236	−0.0800***	−0.0210	−0.0831**	−0.0465**	0.0066***
	(−1.00)	(−0.38)	(−0.83)	(−2.62)	(−0.65)	(−2.30)	(−2.01)	(0.24)
ln(*Price*)	0.3055***	0.6816***	0.2637**	0.3902***	0.4599***	0.3739***	0.2397***	0.7155***
	(2.93)	(5.66)	(2.27)	(3.76)	(3.12)	(4.76)	(3.29)	(5.03)
Turn	−0.1132***	−0.1828***	−0.0991**	−0.0709	−0.2662*	−0.0072	−0.0780***	−0.2220***
	(−2.90)	(3.06)	(−2.04)	(−1.17)	(−1.78)	(−0.64)	(−3.51)	(−3.34)
Volt	0.2979**	0.6143***	0.3044***	0.3500***	0.4327***	0.2419***	0.2623***	0.5702***
	(2.54)	(5.12)	(2.73)	(2.63)	(4.02)	(3.07)	(3.43)	(5.63)
Adjusted R^2	0.0153	0.0195	0.0136	0.0094	0.0163	0.0090	0.0135	0.0197
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust std errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\theta_2^{LOW} - \theta_2^{HIGH}$	0.0003		0.0002		0.0006*		−0.0001	
	(1.12)		(0.77)		(1.79)		(-0.51)	
Panel B. NASDAQ-Listed Stocks								
Intercept	3.2251***	−1.8136***	3.5331***	1.3261	2.8215***	−1.0722	0.8353	1.5349
	(3.87)	(−1.98)	(3.49)	(1.61)	(2.83)	(−1.21)	(0.97)	(1.36)
SUE	0.1202***	0.0971***	0.1387***	0.0778***	0.1532***	0.0627***	0.1126***	0.1113***
	(18.17)	(16.98)	(19.66)	(15.38)	(19.94)	(14.01)	(18.34)	(17.48)
SUE^2	0.0014***	0.0007***	0.0016***	0.0007***	0.0013***	0.0007***	0.0010***	0.0007***
	(4.89)	(2.58)	(5.32)	(3.06)	(3.96)	(3.20)	(3.68)	(2.64)

(Continued)

TABLE 4. Continued.

	Low *InstOwn*	High *InstOwn*	Low *Breadth*	High *Breadth*	Low *Size*	High *Size*	Low *RSI*	High *RSI*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel B. NASDAQ-Listed Stocks (continued)								
ln(*Size*)	−0.2287***	−0.0021	−0.2539***	−0.1486***	−0.1782***	−0.0345	−0.0773**	−0.1694***
	(−6.16)	(−0.06)	(−4.97)	(−4.54)	(−4.00)	(−0.93)	(−1.96)	(−3.13)
ln(*Price*)	0.6871***	0.4690***	0.6058***	0.45497***	0.6224***	0.4946***	0.3553***	0.9581***
	(9.05)	(5.09)	(7.10)	(5.59)	(6.92)	(6.92)	(4.14)	(9.63)
Turn	−0.1709***	−0.1687***	−0.2219**	−0.2171***	−0.2958***	−0.0901***	−0.2219*	−0.1343***
	(−5.17)	(−4.01)	(−6.24)	(−5.72)	(−6.59)	(−3.20)	(−1.82)	(−5.68)
Volt	0.0659*	0.4030***	0.0897**	0.4843***	0.1252***	0.2575***	0.1186**	0.0521
	(1.70)	(4.78)	(2.09)	(6.63)	(2.58)	(4.10)	(2.24)	(0.78)
Adjusted R^2	0.0240	0.0159	0.0258	0.0159	0.0270	0.0118	0.0213	0.0227
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust std errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\theta_2^{LOW} - \theta_2^{HIGH}$	0.0007**		0.0009***		0.0006*		0.0003	
	(2.48)		(2.99)		(1.83)		(1.11)	

Note: The table reports the cross-sectional regression results from estimating the following regression:

$$CAR(0,1)_i = \alpha + \theta_1\, SUE_{i,t} + \theta_2\, SUE_{i,t}^2 + \beta_1 \ln(Size_{i,t}) + \beta_2 \ln(Price_{i,t}) + \beta_3 Turn_{i,t-6,t-1} + \beta_4 Rvolt_{i,t-6,t-1} + \eta_i.$$

The dependent variable is the cumulative abnormal return from day 0 to day 1 (*CAR*(0,1), where day 0 is the earnings announcement date. The independent variables include the standardized unexpected earnings (*SUE*) and the squared term (*SUE*^{2}) associated with the earnings announcement. We also include as control variables the natural log of market capitalization (ln(*Size*)), natural log of the share price (ln(*Price*)), share turnover during the six months preceding the earnings announcement in month *t* (*Turn*), and return volatility during the six months preceding the earnings announcement in month *t* (*Volt*). In response to a Hausman test, we include year fixed effects. *InstOwn* is the number of shares held by institutions scaled by shares outstanding. *Breadth* is the number of institutional shareholders. *Size* is the market capitalization in $ billions. *RSI* is the relative short interest obtained from Compustat. Panel A reports the results for NYSE-listed stocks and Panel B reports the results for NASDAQ-listed stocks. We also estimate the equation for stocks that are constrained according to our proxies (columns [1], [3], [5], and [7]) and stocks that are unconstrained (columns [2], [4], [6], and [8]). The *t*-statistics that control for two-dimensional clustering are reported in parentheses below the corresponding coefficients. At the bottom of each panel, we report low minus high ($\theta_2^{LOW} - \theta_2^{HIGH}$) differences with a corresponding *t*-statistic.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

Column [1] in Panel A of Table 5 shows that for stocks with the least return volatility, the coefficients on *SUE* and SUE^2 are positive. However, the coefficient on SUE^2 is not reliably different from zero. This result suggests that for stocks with the least heterogeneity, the price response to the earnings announcement is linear across the earnings signal. In column [2], we find that the coefficients on *SUE* and SUE^2 are positive and significantly different from zero. The results in column [2] support the theory in Xu (2007) and suggest that stocks with greater heterogeneity drive the convexity observed in NYSE-listed stocks. At the bottom of Panel A, we find that the difference between the magnitude of the coefficients on SUE^2 is reliably different from zero (difference = −0.0008, *t*-statistic = 5.24).

In columns [3] and [4], we find that the coefficients on *SUE* and SUE^2 are positive. Contrary to our expectation, we find that stocks with the least turnover generate a coefficient on SUE^2 that is significant. Furthermore, although stocks with the most turnover (column [4]) produce a positive coefficient on SUE^2 that is slightly greater than the corresponding coefficient for stocks with the least turnover (column [3]), the estimate is not significant at the .10 level (*p*-value =.113). As expected, the *t*-statistic comparing these estimates for SUE^2 is not large enough to reject the null hypothesis of equality (*t*-statistic = −1.26). Therefore, we are able to find only weak evidence that the price convexity we observe generally is driven by stocks with greater heterogeneity.

Panel B of Table 5 shows the results for NASDAQ-listed stocks. We find that the coefficients on *SUE* and SUE^2 are positive and significant in all four columns. However, a closer examination of the coefficients suggests that the coefficient on SUE^2 in column [2] is significantly larger than the corresponding coefficient in column [1] (*t*-statistic = −4.64). This result supports our findings in columns [1] and [2] of Panel A as well as our expectation. When we proxy for heterogeneity using turnover in columns [3] and [4], we again find that the coefficients on *SUE* and SUE^2 are positive and significant and that the difference between the coefficients on SUE^2 is not reliably different from zero (*t*-statistic =.74). These results suggest that only weak evidence exists for the idea that heterogeneity induces greater convexity in NYSE-listed and NASDAQ-listed stocks. However, our evidence in Table 5 depends heavily on the variable we use to proxy for heterogeneous beliefs among investors.

As a measure of robustness, we replicate our analysis but use the Fama–MacBeth (1973) approach with robust standard errors using the typical Newey–West (1987) adjustment. The conclusions we are able to draw are qualitatively similar to those in Tables 3 through 5. In fact, when conditioning the regression results on our proxies for short-sale constraints, we find in each case that the subsample of constrained stocks generates positive and significant estimates for *SUE* and SUE^2, whereas the subsample of stocks that are unconstrained does not. These results hold in both NYSE-listed and NASDAQ-listed stocks. The only exception is for NYSE stocks with the lowest ownership breadth. Here, we do not find that NYSE stocks with low breadth generate a convex price response to earnings surprise. Although the coefficient on *SUE* is positive and statistically significant, the coefficient on SUE^2 is positive but not reliably different from zero (estimate = 0.0003, *t*-statistic = 1.11). The remainder of the proxies used for short-sale constrained stocks show that the convexity we

TABLE 5. Convexity Regressions and Heterogeneous Beliefs.

	Low Volt	High Volt	Low Turn	High Turn
	[1]	[2]	[3]	[4]
Panel A. NYSE-Listed Stocks				
Intercept	−1.1780**	−1.0572	1.2169	−2.0829*
	(−2.14)	(−1.08)	(1.04)	(−1.95)
SUE	0.0380***	0.1016***	0.0411***	0.0882***
	(12.91)	(10.20)	(11.60)	(9.96)
SUE^2	0.0002	0.0010**	0.0005***	0.0007
	(1.31)	(1.98)	(3.14)	(1.59)
ln(*Size*)	−0.0068	−0.0659*	−0.0243	−0.0466
	(−0.46)	(−1.62)	(−1.28)	(−1.21)
Ln(*Price*)	0.1738***	0.6503***	0.1101	0.7159***
	(3.23)	(4.98)	(1.54)	(4.95)
Turn	−0.0642	−0.1099***	−0.4494	−0.0403
	(−0.96)	(−2.98)	(−1.39)	(−1.57)
Volt	0.2372*	0.4630***	0.2838***	0.4470***
	(1.89)	(4.90)	(3.49)	(4.79)
Adjusted R^2	0.0162	0.0167	0.0131	0.0168
Year fixed effects	Yes	Yes	Yes	Yes
Robust std errors	Yes	Yes	Yes	Yes
${\theta_2}^{LOW} - {\theta_2}^{HIGH}$	−0.0008*		−0.0002	
	(−5.24)		(−1.26)	
Panel B. NASDAQ-Listed Stocks				
Intercept	0.0920	4.9819***	2.5285***	−1.1835
	(0.18)	(4.24)	(3.65)	(−1.07)
SUE	0.0566***	0.1427***	0.0997***	0.1196***
	(21.47)	(15.89)	(16.16)	(16.81)
SUE^2	0.0006***	0.0013***	0.0011***	0.0009***
	(5.16)	(3.36)	(4.12)	(2.58)
ln(*Size*)	−0.0565***	−0.3134***	−0.1101***	−0.0380
	(−3.02)	(−5.38)	(−3.39)	(−0.79)
ln(*Price*)	0.3056***	0.9462***	0.0083	0.9784***
	(5.76)	(9.47)	(0.09)	(11.09)
Turn	−0.0285	−0.1846***	−1.5896**	−0.0934***
	(−1.00)	(−7.06)	(−2.56)	(−4.26)
Volt	0.1580*	0.0892**	0.1299**	0.0173
	(1.84)	(2.12)	(2.07)	(0.36)
Adjusted R^2	0.0188	0.0214	0.0196	0.0245
Year fixed effects	Yes	Yes	Yes	Yes
Robust std errors	Yes	Yes	Yes	Yes
${\theta_2}^{LOW} - {\theta_2}^{HIGH}$	−0.0007***		0.0002	
	(−4.64)		(0.74)	

Note: The table reports the cross-sectional regression results from estimating the following regression:

$$CAR(0,1)_i = \alpha + \theta_1\, SUE_{i,t} + \theta_2\, SUE_{i,t}^2 + \beta_1 \ln(Size_{i,t}) + \beta_2 \ln(Price_{i,t}) + \beta_3 Turn_{i,t-6,t-1} + \beta_4 Rvolt_{i,t-6,t-1} + \eta_i.$$

The dependent variable is the cumulative abnormal return from day 0 to day 1 (*CAR*(0,1)), where day 0 is the earnings announcement date. The independent variables include the standardized unexpected earnings (*SUE*) and the squared term (SUE^2) associated with the earnings announcement. We also include as control variables the natural log of market capitalization (ln(*Size*)), the natural log of the share price (ln(*Price*)), share turnover during the six months preceding the earnings announcement in month *t* (*Turn*), and return volatility during the six months preceding the earnings announcement in month *t* (*Volt*). In response to a Hausman test, we include year fixed effects. Panel A reports the results for NYSE-listed stocks and Panel B reports the results for NASDAQ-listed stocks. We also estimate the equation for stocks with less heterogeneity according to our proxies (columns [1] and [3]) and stocks with greater heterogeneity (columns [2] and [4]). The *t*-statistics that control for two-dimensional clustering are reported in parentheses below the corresponding coefficients. At the bottom of each panel, we report low minus high (${\theta_2}^{LOW} - {\theta_2}^{HIGH}$) differences with a corresponding *t*-statistic.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

observe is generally driven by stocks that are the most likely to face constraints. When we replicate Table 5 using Fama–MacBeth regressions, we do not find that NYSE-listed stocks with the most return volatility drive the convexity that we observe generally. As reported above, our ordinary least squares (OLS) results provide only weak evidence that heterogeneity drives the convexity. However, this weak evidence is not robust to Fama–MacBeth regressions. Therefore, we exercise further caution when drawing meaningful inferences about the association between heterogeneity and price convexity. It is important to note that the Fama–MacBeth approach produces mean cross-sectional estimates. We therefore choose to report the OLS regression results because we use time-series estimates (by stock) of convexity to test our second hypothesis. These tests are presented next.

Relation between Skewness and Convexity

In this subsection, we examine the relation between skewness and convexity in attempt to test our second hypothesis that skewness is directly related to the convex price response to earnings announcements. We begin estimating the following cross-sectional regression and report the results in Table 6:

$$\begin{aligned} Skew_i = \beta_0 &+ \beta_1 \ln(Price_i) + \beta_2 B/M_i + \beta_3 Rvolt_i + \beta_4 Turn_i + \beta_5 \ln(Size_i) \\ &+ \beta_6 \ln(InstOwn_i) + \beta_7 \ln(Breadth_i) + \beta_8 \theta_{1i} + \beta_9 \theta_{2i} + \varepsilon_i. \end{aligned} \quad (4)$$

The dependent variable is the average skewness for each stock i (*Skew*). The independent variables include the natural log of the average share price ($\ln(Price_i)$), book-to-market ratio (B/M_i), return volatility ($Rvolt_i$), share turnover ($Turn_i$), natural log of market cap ($\ln(Size_i)$), natural log of institutional ownership ($\ln(InstOwn_i)$), and natural log of ownership breadth ($\ln(Breadth_i)$). The variables of interest are the coefficients from estimating equation (3) by stock. In particular, the independent variables of interest are the estimated coefficients on *SUE* and the squared term SUE^2. To the extent that price convexity influences the skewness of stock returns, we expect that the estimated coefficient particularly on SUE^2 to be directly related to skewness. We report t-statistics that are obtained from White (1980) standard errors in parentheses. As before, we estimate equation (4) for NYSE- and NASDAQ-listed stocks separately. Results for the sample of NYSE-listed stocks are reported in columns [1] through [4] and results for NASDAQ-listed stocks are provided in columns [5] through [8].

We note that the independent variables that have been averaged across time for each stock are highly collinear. To examine the effect of multicollinearity, we estimate variance inflation factors and find that size, institutional ownership, and ownership breadth have highly inflated standard errors because of collinearity (variance inflation factors are well above 10 for these three variables). Therefore, we estimate variants of equation (4) and only include one of these three independent variables at a time. We also report the full model in columns [4] and [8] but exercise caution in drawing inferences from these specifications because of the high level of multicollinearity.

Focusing on NYSE-listed stocks, we generally find that skewness is directly related to book-to-market ratios and return volatility but negatively related to turnover.

TABLE 6. Cross-Sectional Regression Results.

	NYSE-Listed Stocks				NASDAQ-Listed Stocks			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.5374***	0.0142	0.3759***	0.4205**	1.1992***	−0.4926***	0.2159***	0.1911
$Price_i$	−0.0217	−0.0433	0.0260	0.0273	0.0697***	0.0245	0.0745***	0.0738***
	(−0.75)	(−1.60)	(0.85)	(0.87)	(3.83)	(1.47)	(4.31)	(4.18)
B/M_i	0.0207***	0.0279***	0.0244***	0.0250***	−0.1797*	0.0136	0.1263***	0.0921
	(6.90)	(19.45)	(16.05)	(6.29)	(−1.69)	(0.61)	(3.92)	(1.66)
$Rvolt_i$	0.1593***	0.1691***	0.1631***	0.1605***	0.2639***	0.2568***	0.2495***	0.2476***
	(4.99)	(5.27)	(5.25)	(5.20)	(18.52)	(17.34)	(17.87)	(17.79)
$Turn_i$	−0.0406**	−0.0527***	−0.0410***	−0.0388**	−0.0074	−0.0130	0.0128	0.0126
	(−2.34)	(−3.03)	(−2.68)	(−2.50)	(−0.66)	(−1.20)	(1.18)	(1.15)
$\ln(Size_i)$	−0.0260***			0.0011	−0.0870***			−0.0052
	(−3.37)			(0.10)	(−9.57)			(−0.40)
$\ln(InstOwn_i)$		−0.0329***		0.0143		−0.1334***		−0.0288
		(-3.35)		(0.80)		(−8.52)		(−1.27)
$\ln(Breadth_i)$			−0.1154***	−0.1271***			−0.1792***	−0.1527***
			(−6.22)	(−4.50)			(−12.31)	(−5.01)
θ_{1i}	−0.0064	−0.0058	−0.0064	−0.0065	0.0077	0.0104	0.0074	0.0076
	(−1.22)	(−1.06)	(−1.25)	(−1.28)	(0.87)	(1.15)	(0.80)	(0.83)
θ_{2i}	0.0025**	0.0028***	0.0028**	0.0027***	−0.0162*	−0.0082	−0.0144	−0.0132
	(2.73)	(2.78)	(2.85)	(2.85)	(−1.74)	(−0.92)	(−1.56)	(−1.43)
Adj R^2	0.1515	0.1485	0.1797	0.1791	2,950	2,950	2,950	2,950
N	1,270	1,270	1,270	1,270	0.3349	0.3369	0.3570	0.3570

Note: The table reports the results from estimating the following equation using cross-sectional data that has been averaged for NYSE stocks (in columns [1] through [4]) or across NASDAQ stocks (columns [5] through [8]):

$$Skew_i = \beta_0 + \beta_1 \ln(Price_i) + \beta_2 B/M_i + \beta_3 Rvolt_i + \beta_4 Turn_i + \beta_5 \ln(Size_i) + \beta_6 \ln(InstOwn_i) + \beta_7 \ln(Breadth_i) + \beta_8\ \theta_{1i} + \beta_9\ \theta_{2i} + \varepsilon_i.$$

The dependent variable is the average skewness for each stock during the bubble period or the postbubble period (*Skew*). The independent variables include the average share price ($Price_i$), book-to-market ratio (B/M_i), return volatility ($Rvolt_i$), share turnover ($Turn_i$), natural log of market cap ($\ln(Size_i)$), natural log of institutional ownership ($\ln(InstOwn_i)$), and natural log of ownership breadth ($\ln(Breadth_i)$). The variables of interest are the coefficients from estimating the following equation:

$$CAR(0,1)_i = \alpha + \theta_1\, SUE_{i,t} + \theta_2\, SUE_{i,t}^2 + \beta_1 \ln(Size_{i,t}) + \beta_2 \ln(Price_{i,t}) + \beta_3 Turn_{i,t-6,t-1} + \beta_4 Rvolt_{i,t-6,t-1} + \eta_i.$$

The dependent variable is the cumulative abnormal return from day 0 to day 1 (*CAR*(0,1)), where day 0 is the earnings announcement date. The independent variables include the standardized unexpected earnings (*SUE*) and the squared term (SUE^2) associated with the earnings announcement. We also include as control variables the natural log of market capitalization (ln(*Size*)), the natural log of the share price (ln(*Price*)), share turnover during the six months preceding the earnings announcement in month *t* (*Turn*), and return volatility during the six months preceding the earnings announcement in month *t* (*Volt*). The independent variables of interest are the coefficients on *SUE* and the squared term SUE^2. We report *t*-statistics that are obtained from White (1980) standard errors in parentheses.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

Furthermore, we find that market capitalization is negatively related to skewness (column [1]), institutional ownership is negatively related to skewness (column [2]), and ownership breadth is negatively related to skewness (column [3]). The regression results from these control variables are generally consistent with findings in Xu (2007) with the exception of turnover. Again, Xu assumes that turnover properly captures heterogeneity but we find that turnover is negatively related to skewness. Focusing now on our independent variables of interest, we do not find that the estimated coefficient on *SUE* produces a reliable estimate. However, consistent with our second hypothesis, we find that the estimated coefficient on SUE^2 does directly influence the skewness of returns. These results hold in each of the first three columns and support our second hypothesis that the degree of price convexity (the magnitude of the coefficient on SUE^2) increases the skewness in the return distribution. Results in column [4] are qualitatively similar to those in the previous columns as the coefficient on θ_{2i} is positive and significant (estimate = .0027, *t*-statistic = 2.85). Furthermore, when we include each of the proxies for short-sale constraints used in Xu we find that only ownership breadth is negatively related to skewness. We raise caution in drawing meaningful conclusions about these results given the high level of multicollinearity between the constraints proxies.

Next, we estimate equation (4) for the sample of NASDAQ-listed stocks. Results are reported in columns [5] through [8] of Table 6. We do not find evidence consistent with our second hypothesis as the coefficients on θ_1 and θ_2 are not reliably different from zero. These nonsignificant estimates are reported in each of the last four columns. As a side note, we again find that market capitalization, institutional ownership, and ownership breadth are each negatively related to skewness (in columns [5] through [7]), which is consistent with findings in Xu (2007). Consistent with the results from the NYSE sample, we find in column [8] that when including each of the constraint proxies, only ownership breadth produces a reliably negative estimate. As before, we are cautious drawing any inferences in this last column as we observe unusually high multicollinearity between the constraint proxies. In sum, we are only able to find support for our second hypothesis in the sample of NYSE-listed stocks.

V. Conclusion

A growing body of research has examined the implications of skewness in the return distributions of stocks. Such skewness can adversely affect the results of asset pricing tests, which rest on the assumption of normality. Furthermore, more recent research argues that some investors have strong preferences for skewness, which might resemble the distributional characteristics of lotteries. These preferences can create price premiums and subsequent underperformance (Barberis and Huang 2008; Mitton and Vorkink 2007; Kumar 2009; Boyer, Mitton, and Vorkink 2010; Kumar, Page, and Spalt 2011). To the extent that skewness can affect asset pricing models and stock prices more generally, identifying factors that lead to more skewness can provide an important contribution to the literature.

Following the theoretical predictions in Xu (2007), which identify some potential factors that influence return skewness, this study examines an important asymmetry in postearnings announcement stock prices. Xu argues that in the presence of short-sale constraints and heterogeneous beliefs among investors, prices will respond more to good news than to bad news. This asymmetric response to the news signal will create convexity in the postsignal returns. We first test whether convexity in the price response to earnings announcements increases as short-sale constraints become tighter and as the degree of investor disagreement increases. Consistent with our expectation and the theoretical predictions in Xu, our univariate sorts and our multivariate tests generally show that short-sale constraints drive the convex price response to earnings announcements. Results further show that the direct association between price convexity and heterogeneous beliefs is weak at best.

A natural extension to these findings is to determine whether price convexity in the postannouncement period directly affects skewness. Given that skewness is a convex transformation, we expect a positive relation between the degree of price convexity and the level of return skewness. Results from our second set of tests show that for our sample of NYSE-listed stocks, skewness relates positively to the degree of convexity in postannouncement returns. We do not find, however, that this relation holds for our sample of NASDAQ-listed stocks. In general, our findings are consistent with the idea that short-sale constraints influence the degree of price convexity during the postannouncement period, and to a less extent, price convexity influences the level of skewness in the distribution of stock returns.

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