# Are unexpected earnings predictable?

**Abstract**

We investigate whether information extracted from trading activities in the equity options markets can be used to forecast unexpected earnings. Employing a sample of all firm quarterly earnings between 1996 and 2012 in the United States, we document evidence that implied volatility smirk in the options markets have significant prediction power of standardized unexpected earnings. Furthermore, the predicability is stronger for NASDAQ firms than for NYSE firms and is stronger over the post-SOX period than over the pre-SOX period. Moreover, implied volatility smirk predicts both short- and long-term cumulative abnormal returns following an earnings announcement.

"A windfall bet made in H.J. Heinz Co. options one day before a buyout was announced Thursday prompted regulators to act quickly, freezing assets they suspect are tied to the trade." (*The Wall Street Journal, February 18, 2013*)

"The Federal Bureau of Investigation has begun a criminal investigation into a big options trade made the day before last week's announcement of the blockbuster $23 billion buyout of H.J. Heinz Co." (*The Wall Street Journal, February 19, 2013*)

## 1. Introduction

The suspicious trading of H.J. Heinz options right before its public disclosure of an important corporate event that moves stock price is not an isolated, nor a unprecedentedly peculiar, incidence on the Wall Street. For instance, just two weeks later, the Wall Street Journal reported that Bank of America profited in the summer of 2012 from a big options position it built ahead of the announcement of an corporate acquisition deal in which the bank was the lead lender.[1] Over the past several years, the public, as well as the regulators, have drawn increasing attention to such alleged insider cases in the options markets.[2]

Indeed, since 2011 the SEC has filed 168 insider trading actions against nearly 400 individuals and entities with about $600 million at stake, setting a record in any similar period in agency's history.[3] However, the vast majority of charges have been concerning wrongful trading in the stocks market while there were only a few allegations or settlement with SEC regarding the allegedly illegal trading activities in the options markets. Between 2009 and 2011, the SEC took merely seven cases against illicit use of options contracts surrounding major corporate events.[4] Because of the rather complicated trading rules for options and fairly decentralized trading venues in which the sophisticated options traders can exercise their hiding tactics often in the name of hedging, regulators so far appeared hesitant to initiate more inquiries into the suspicious options trading. After all, there is also a lack of systematic examination that provides empirical evidence on the issue of

[1] "BofA times an options trade well," *The Wall Street Journal*, March 6, 2013.

[2] Such as Nexen Inc., Youku Inc., Human Genome Science Inc., Constellation Brands Inc., CBS Corp., Baxter International, Bank of America's acquisition of Countrywide Financial, etc.

[3] Lindeman, Teresa F., "SEC continues probe of suspicious trading of H.J. Heinz stock, Swiss account," in *Pittsburgh Post-Gazette*, April 4, 2013.

[4] Kaitly N. Kiernan, "Options activity questioned again," *The Wall Street Journal*, February 18, 2013.

how pervasive and persistent is such well-timed trade in the options markets over years, especially in response to the recent major regulatory shake-ups. Our paper intends to fill the void.

We focus on one particular type of corporate news events, quarterly earnings announcements, as the objects of our investigation. Our research question is simple and straightforward: Does the options market have any systematic forecasting power to the subsequent earnings realization of the corporate beyond any other reasonable explanations? More specifically, we use the implied volatility smirk to summarize the aggregate perception in the options market about the potential deviation of actual earnings from its market expectation, i.e., unexpected earnings. If the realization of such deviation, measured by the most recent analyst forecast errors, are truly surprises to the market, we should not expect options market to offer any systematic and consistent predictability to these unexpected earnings. Unless one is convinced that options traders have always outsmarted equity analysts when being fed with identical, legally available information in the market, you can hardly resist the notion that options traders are *even* better-informed than the already information-advantageous financial analysts. Through a series of empirical exercises, we do find significant and persuasive evidence that options traders were smart enough to consistently forecast the unexpected over the last seventeen years.

Furthermore, we wonder such "smartness" differs across market environments subject to heterogeneous regulatory oversight and disparate mandatory requirements on information disclosure, namely the New York Stock Exchange and the NASDAQ. If it is truly the incompetence of equity analysts to interpret the publicly available information, we wouldn't expect any difference in predictability of options market to earnings surprises between the two market places. On the other hand, if it is due to the private information exclusively flowing to options traders, we would observe stronger predictability for the NASDAQ firms that receive fewer regulatory and analyst scrutinies and whose corporate governance and disclosure requirements were chronically weaker than their NYSE peers (Kelton and Yang, 2008; Pincus, Rusbarsky, and Wong, 1989). Weaker corporate governance makes information leakage or insider tipping more likely to occur while the regulatory arbitrage entices informed-trade into the market with relatively lax regulatory oversight. Our empirical evidence unequivocally points to the latter explanation.

Finally, we utilize the most recent regulatory reform, such as Reg FD and Sarbane-

Oxley Act, as a natural experiment to examine how the informed-trade in options market has responded. The U.S. regulators introduced a number of legislature measures that intended to level the ground for all investors either through more equal sharing of the corporate information in Reg FD or through more severe penalty on the misconduct of corporate executives in Sarbanes-Oxley Act. Because of more transparent, frequent, and timely communications between public firms and investors, we would expect a cross-board, tremendous reduction in the information advantage for the previously well-informed investors, including options traders. Therefore the options trade would be less informative to predict the upcoming earnings surprises. At the same time, informed traders faced more comprehensive scrutinies than ever on their trading activities before almost any corporate events that release material information. They would more cautiously exploit their information advantage and choose the relatively "safe" type of securities to trade. In comparison to stock trading, suspicious options trading activities are both easier to hide and less conspicuous to draw the public, hence regulator's, attention. It is also likely that regulatory arbitrage pushes more informed traders into the options market after the legislature was enacted, which indicates an even stronger predictability in more recent year. It turns out informed traders still played the old game, even more lively, in the options market than before.

The paper proceeds as follows. We review the related literature in section 2. Section 4 describes our research methodology and the data. We present the empirical results in section 5 and conclude in section 6.

## 2. Related Literature

Our paper combines insights from two strands of literature. One stream of literature document a close linkage between the options and stock markets, especially the lead-lag price discovery process due to the choice of trading locations by investors of different sophistication levels. On the theoretical side, Black (1975) argues that options market is often preferred by traders who have private information to take advantage of in a market with reduced transaction costs, increased financial leverage, and a lack of short-selling constraints. Easley, O'Hara, and Srinivas (1998) suggests that informed traders are more likely to trade in the option, rather than the stock, markets if the the leverage or liquidity in the options is high, if the liquidity in the underlying stock is low, or if there are already a large informed investors base in the stock market. There is however no mention of the regulatory aspect to drive the preference of informed traders towards either market.

On the empirical side, a large number of studies have provided supportive evidence of strong predictive power of different measures in options markets for stock returns, such as Manaster and Rendleman (1982), Anthony (1988), Finucane (1991), Chakravarty, Gulen, and Mayhew (2004), Holowczak, Simaan, and Wu (2006), Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Doran and Krieger (2010), and Goyal and Saretto (2009).[5] The information diffusion from the options market to the underlying equity markets can be gradual (Chan, Kot, and Ni, 2010) and implies exploitable trading strategies for equity investors (Baltussen, van der Grient, de Groot, Hennink, and Zhou, 2012). In particular, the options markets are more conducive than the stock markets to information and price discovery prior to important corporate events, such as M&A announcements (Cao, Chen, and Griffin, 2005; Jayaraman, Frye, and Sabherwal, 2001), earnings disclosures (Amin and Lee, 1997; Billings and Jennings, 2011; Hao, Lee, and Piqueira, 2013; Jin, Livnat, and Zhang, 2012; Schachter, 1998), or analysts' forecast revisions (Hayunga and Lung, forthcoming; Lin, Lu, and Driessen, 2013).[6] In general, Sinha and Dong (2011) observe dramatic increase, almost seven times more than normal times, in the trading volume of options prior to the news arrivals in contrast to the modest increase by 17% in the volume of stock trading. Xing, Zhang, and Zhao (2010) further propose a measure of options smirk that exactly reflects the worries of informed traders about negative price movements of underlying stocks due to the upcoming negative news event.

Another potentially important, institutional factor that magnetizes informed traders to exploit their informational advantage in options markets is the regulatory arbitrage resulting from the inadequacy of regulatory oversight in the options market relative to the stock market. There is so far very limited and mostly anecdotal evidence from the enforcement actions by the U.S. Securities and Exchange Commission supporting the

[5] There is also contradictory evidence. Chan, Chung, and Fong (2002) find that stock market leads the options market and Muravyev, Pearson, and Paul Broussard (2013) find no economically significant information in options price quotes about future stock prices in 39 liquid U.S. stocks.

[6] Recent finding of Hong, Schonberger, and Subramanyam (2013) objects the notion that predictable patterns in future stock returns associated with accounting anomalies such as post-earnings-announcement-drift, working capital accruals, net operating assets, and changes in net operating asset turnover have been factored in the options prices.

regulatory view of information diffusion across the markets.[7] This paper, therefore, fills the void in the literature to supply fresh evidence on whether the documented lead-lag price discovery process between the options and equity markets is partially attributable to the regulatory differentials across the market and over time.

The other strand of insightful literature examine the information content of the *ex ante* publicly available options market measures around earnings announcements. Early work of Patell and Wolfson (1979, 1982) document the abnormal increases in the option's implied volatility just ahead of the earnings release. Skinner (1990) has demonstrated that firms' earnings surprises became less informative to the stock markets after the listing of exchange-traded options for the underly stocks. Ni, Pan, and Poteshman (2008) observe a tremendous increase in the price sensitivity to the demand for volatility in the options market in the days leading up to earnings announcements and a quick decline to its normal level soon after the releases. Billings and Jennings (2011) develop a measure from options prices that anticipates the information of approaching earnings announcement and thus significantly correlates with the *ex post* magnitude of stock price responses to the unexpected earnings. This finding particularly inspires the focus of our empirical scrutiny on the information content of options market measures prior to earnings releases as a predictor to the subsequent analysts' earnings forecast errors (or earnings surprises) in the context of examining the impact of regulatory differentials on the extent of informed trading between the options and equity markets. Following the accounting literature that analyzes the analysts' forecasting errors (Brown, Richardson, and Schwager, 1987; Higgins, 2013), we control for a set of conventional explanatory variables that summarize information environment of a firm such as log of firm size, dispersion of analyst earnings forecast, volatility in firm earnings, market-to-book ratio, and analyst coverage, etc.

We next formulate the a series of hypothesis to examine whether the unexpected earnings are actually expected by options traders and how much the anticipation of the "unexpected" varies by the regulatory environments across markets or over time.

[7] See references in Section (1)

## 3. Data and Research Methodology

### *3.1. Data*

Our sample includes all firms with quarterly earnings information at Compustat, options data at RiskMatrics, and analyst forecast data at IBES between 1996 and 2012. Our final sample includes 72,289 quarterly earnings.

### *3.2. Skews*

Following Xing et al. (2010), we calculate our implied volatility smirk measure for firm $i$ at week $t$, $\mathrm{SKEW}_{i,t}$, as the difference between the implied volatilities of OTM puts and ATM calls, denoted by $\mathrm{VOL}_{i,t}^{OTMP}$ and $\mathrm{VOL}_{i,t}^{ATMC}$, respectively. That is,

$$SKEW_{i,t} = VOL_{i,t}^{OTMP} - VOL_{i,t}^{ATMC} \tag{1}$$

We lag SKEW by one week to get $\mathrm{SKEW}_{\mathrm{lag}}$.

$\mathrm{SKEW}^{vw}$: we compute a volume-weighted volatility skew measure, where we use options trading volumes as weights to compute the average implied volatilities for OTM puts and ATM calls for each stock each day. Both SKEW and $\mathrm{SKEW}^{\mathrm{vw}}$ are calculated during a window of $t-7$ and $t-1$, where $t$ denotes the earnings announcement date. $\mathrm{SKEW}_{\mathrm{lag}}$ is calculated during a window of $t-14$ and $t-8$.

### *3.3. Unexpected earnings*

We measure unexpected earnings using two commonly used definitions of standardized unexpected earnings (SUEs) (Livnat and Mendenhall, 2006). Both $\mathrm{SUE}_1$ are $\mathrm{SUE}_2$ are calculated as the difference between a measure of analysts' expectations and IBES reported actual earnings, scaled by the standard deviation analyst forecasts. In $\mathrm{SUE}_1$ and $\mathrm{SUE}_2$, we measure the analysts' expectations using the median and mean, respectively, of latest individual analysts forecasts issued within the 90 days prior to the EAD. The cumulative abnormal returns, $\mathrm{CAR}[x, y]$, are the sum of characteristic risk-adjusted abnormal returns accumulating from $t + x$ to $t + y$, where $t$ denotes the earnings announcement date. To perform size and book-to-market ratio risk adjustment, we follow the procedure laid out at Professor Kenneth French's web site.

Following previous studies, including Chordia, Goyal, Sadka, Sadka, and Shivakumar (2009), Jegadeesh and Livnat (2006), and You and Zhang (2009), we use the standardized unexpected earnings (SUE) as ours measures of unexpected earnings.

We estimate SUE as the difference between actual earnings per share and median (or mean) analyst forecasts, scaled by the dispersion of analyst forecasts:

$$\mathrm{SUE}_{h,t} = \frac{EPS_{h,t} - FEPS_{h,t}}{STD(FEPS_{h,t})}, \tag{2}$$

where $FEPS_{h,t}$ is analysts' expectations. In $\mathrm{SUE}_1$ and $\mathrm{SUE}_2$, we measure the analysts' expectations using the median and mean, respectively, of latest individual analysts forecasts issued within the 90 days prior to the EAD (Livnat and Mendenhall, 2006).

### *3.4. Firm characteristics*

BETA measures the systematic risk, calculated from the standard market model. VAR is idiosyncratic return volatility calculated as the standard deviation of the residuals from the Fama-French (1993) model, following Ang, Hodrick, Xing, and Zhang (2006). To calculate VAR, we require at least 15 trading days of non-missing returns data. Book-to-market equity (MB) is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. SIZE is the logged value of the product of monthly closing price and the number of outstanding shares in June. SPR is the bid-ask spread calculated from CRSP, following Chung and Zhang (2013). SUV is the standardized unexplained volume from Garfinkel (2009). DTO is the market-adjusted turnover de-trended by its 180 trading day median, following Garfinkel (2009) and Anderson and Dyl (2005).

## 4. Empirical Results

### *4.1. Univariate analysis*

Table 1 reports the summary statistics of earnings surprises, implied volatility smirk, and cumulative abnormal returns. Panel A reports the results from univariate analysis and Panel B reports the correlation coefficients among the variables.

From Panel A, we notice that the means for four versions of SKEW are similar, all in the range of 0.0307 and 0.0353. Their standard deviations are all about 1.4 times of the means, indicating significant variability in the sample. The measure of earnings surprises based on the analyst forecasts, SUE, has a mean of 0.0001. The average of CAR$[0,1]$ is 4 basis point, indicating a slightly positive returns over the two day window following an earnings announcement. The 1st and 3rd quartiles of CAR$[0,1]$ are $-3.36\%$ and $3.75\%$, respectively, reflecting the substantial variation in reactions to surprises from earnings news. The magnitudes and signs of SUE and CARs are similar to those reported in the literature (See, for example, Livnat and Mendenhall, 2006; Zhou and Zhu, 2012). The 1st and 3rd quartiles of both CAR$[2,40]$ and CAR$[2,60]$ are consistent with the post-earnings drift reported in the literature.

Insert Table 1 about here.

In Panel B, we notice a relatively low but significantly negative correlation between four measures of implied volatility smirk (SKEW) and SUE, as well as between measures of implied volatility smirk (SKEW) and cumulative abnormal return (CAR). For example, the correlation coefficient between $\text{SKEW}_1$ and SUE is $-0.0337$, which is statistically significant at 1%. The relatively low but statically significant level of correlation indicates a strong connection between SKEW and SUE and between SKEW and CAR, as well as the impact of other unobservable variables on SKEW, SUE and CAR.

### *4.2. Portfolio analysis*

We next examine our main research question: whether traders in the options market can foresee the nature of future corporate events such as the earnings announcements. Specifically, we examine whether the implied volatility smirk observed in the options market ahead of upcoming quarterly earnings announcements is a good predictor to the earnings surprises realized afterwards?

For each calendar quarter between 1996:Q1 and 2012:Q4, we sort stocks into quintile portfolios by ranking firms based on their implied volatility smirks right before the earnings announcement days in the current quarter. We calculate the averages of SUE and CARs in each quintile portfolio, as well as the average of the differences between the lowest and highest quintile portfolios ($Q1 - Q5$). We report the results based on three measures of implied volatility smirks, SKEW, $\text{SKEW}_{\text{lag}}$ and $\text{SKEW}_{\text{vw}}$ in Panel A, B, and C of Table 2, respectively.

Insert Table 2 about here.

In Panel A, the average SUE in the lowest ($Q_1$) quintile portfolio is 0.0005 and that in the highest ($Q_5$) quintile portfolio is $-0.0001$. The average value of SUE in the SKEW $Q_1 - Q_5$ portfolio is 0.0006, statistically significant at 1%. We calculate SKEW over $[t-7, t-1]$ and SUEs over $[t-90, t-1]$, where $t$ denotes the date of earnings announcement. The overlap in the calculation periods of SKEW and SUE and the substantial value of SUE in the SKEW $Q_1 - Q_5$ portfolio suggest that financial analysts may not fully adjust their earnings forecasts by incorporating information available in the options markets.

More strikingly, the average CAR$[0, 1]$ in the SKEW $Q_1 - Q_5$ portfolio is 0.4868%, statistically significant at 1%. Similarly, the average CAR$[2, 40]$ and CAR$[2, 60]$ in the SKEW $Q_1 - Q_5$ portfolio are 0.5513% and 0.9447%, respectively. Given that SKEWs are calculated over the one-week period prior to an earnings announcements, such persistent and significant differences between the two portfolios constitute another type of the puzzling post-earnings-announcement-drifts, indicating a substantial delay for the stock market to react to information contained in the trading activities of the options markets.

One concern is that the results reported in Panel A may be driven by procedural delays in financial analysts' updating or revising their earnings forecasts; consequently, the reported earnings estimates by analysts do not fully reflect the market updates. To address the concern, we repeat our analysis in Panel B where SKEW$_{\text{lag}}$ is used to sort stocks into quintile portfolios. SKEW$_{\text{lag}}$ is calculated over $[t - 14, t - 8]$ and thus there is a one-week window for analysts to update and report any revisions to their earnings forecasts, which enables them to fully incorporate analysis of the trading activities in the options markets. The average SUE and CARs in the SKEW$_{\text{lag}}$ $Q_1 - Q_5$ portfolio are similar to those reported in Panel A.

We next repeat the above portfolio analysis using value-weighted SKEW and report the results in Panel C. The results are similar to those reported in Panels A and B, with slighter greater average SUE and CARs in the SKEW$_{\text{vw}}$ $Q_1 - Q_5$ portfolio. For example, the average CAR$[2, 60]$ in the SKEW$_{\text{vw}}$ $Q_1 - Q_5$ portfolio more than doubles the value reported in Panel B, and is about 1.5 times of the value reported in Panel A.

In summary, the results reported in the three panels of Table 2 forcefully suggest that SKEW is a leading indicator for both SUEs and CARs.

We next address the concern that the results in Table 2 may be driven by some firm characteristics that are correlated with SKEW and examine the averages of SUE in the SKEW $Q_1 - Q_5$ portfolio within each firm-characteristic quintile portfolio. In each calendar quarter, we first sort stocks into five equal-sized portfolios by ranking firms according to one of the following measures: market beta, firm size, market-to-book ratio, short-term momentum, and idiosyncratic return volatility. Within each firm characteristic quintile portfolio, we further sort stocks into five equal-sized portfolios by ranking firms based on their SKEW (or $\text{SKEW}_{\text{lag}}$).

Insert Table 3 about here.

The first three columns of Table 3 report the average SUE in the lowest and highest quintile portfolios (SKEW Q1 and Q5, respectively), as well as the average of SUE differences between the two portfolios, within each of the quintile portfolios sorted on one firm characteristic: market beta (Panel A), firm size (Panel B), market-to-book ratio (Panel C), short-term momentum (Panel D), and idiosyncratic return volatility (Panel E). None of these firm characteristics can fully account for the significant correlation between the ex-ante implied volatility smirk and the ex-post unexpected earnings. For example, as we observe in Panel A, the average earnings surprises in the SKEW $Q1-Q5$ portfolios are statistically significant in three (i.e., Q1, Q2, and Q4) of the five beta-sorted quintile portfolios. The average unexpected earnings in the SKEW $Q1 - Q5$ portfolio within the BETA $Q1$ portfolio is 0.0010 , statistically significant at 1%. Similar results are observed in the remaining four panels. The last three columns of Table 3 report the results based on $\text{SKEW}_{\text{lag}}$ and the results are similar to those when SKEW is used as the ranking variable.

The above results partially rule out the possibility that the significant difference in unexpected earnings between the lowest and highest SKEW-sorted quintile portfolios are attributable to common firm characteristics. It thus provides preliminary evidence supporting our hypothesis that options traders foresee the nature of future corporate events such as the earnings announcements.

*4.3. Regression analysis*

$$
\begin{aligned}
\mathrm{SUE}_{it} = \alpha_0 \quad &+ \quad \beta_1\mathrm{SKEW}_{it} + \beta_2\mathrm{RET1M}_{it} + \beta_3\mathrm{RET3M}_{it} + \beta_4\mathrm{BETA}_{i,t} + \beta_5\mathrm{VAR}_{it} \\
&+ \quad \beta_6\mathrm{MB}_{it} + \beta_7\mathrm{SIZE}_{it} + \beta_8\mathrm{SPR}_{it} + \beta_9\mathrm{SUV}_{it} + \beta_{10}\mathrm{DTO}_{it} \\
&+ \quad \alpha_1\mathrm{EXCH}_i + \sum_{j=2}^{10}\lambda_j\mathrm{SIC}_j + \sum_{k=1997}^{2011}\gamma_k\mathrm{YR}_k + \sum_{m=2}^{12}\theta_m\mathrm{MO}_m + \varepsilon_{it} \qquad (3)
\end{aligned}
$$

Multivariate regression analysis provides us with more substantial evidence of the implied volatility smirk having predictive power to the surprises revealed in subsequent corporate news releases. We consider two measures of implied volatility smirk in regressions and apply three estimation methods — pooled cross-sectional OLS, panel regression with firm-specific fixed effect, and Fama-MacBeth two-stage procedure. The dependent variable is unexpected earnings, measured by SUE. In addition to SKEW, we include an array of firm characteristics as control variables. RET1M and RET3M are the compound gross stock returns over the previous one and three months period prior to the date of earnings announcement. BETA measures the systematic risk, calculated from the standard market model. VAR is idiosyncratic return volatility calculated as the standard deviation of the residuals from the Fama-French (1993) model, following Ang et al. (2006). To calculate VAR, we require at least 15 trading days of non-missing returns data. Book-to-market equity (MB) is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity, both from the previous calendar year. SIZE is the logged value of the product of monthly closing price and the number of outstanding shares in June. SPR is the bid-ask spread calculated from CRSP, following Chung and Zhang (2013). SUV is the standardized unexplained volume from Garfinkel (2009). DTO is the market-adjusted turnover de-trended by its 180 trading day median, following Garfinkel (2009) and Anderson and Dyl (2005).

Insert Table 4 about here.

We report the estimation results based on SKEW and $\mathrm{SKEW}_{\mathrm{lag}}$ in Columns 1–3 and 4–6 of Table 4, respectively. In Columns 1–3, the estimated coefficients on SKEW are all negative and statically significant at 1% in all three model specification, suggesting that

SKEW has strong marginal predictive power to unexpected earnings after controlling other firm characteristics that may also contribute to the prediction of unexpected earnings. For instance, a one standard deviation change of 0.0433 in the measure of SKEW, based on our pooled cross sectional estimation in column (1), predicts an average decrease of 0.0006 in the measure SUE whose sample range between the 25% and 50% percentile is merely 0.0004. Among the control variables, we document that long-term past stock returns (RET3M) are positively correlated with unexpected earnings, but not short-term past stock returns (RET1M). Firm size and standardized unexplained volume help to explain unexpected earnings. There is no obvious evidence for other firm characters to predict unexpected earnings. When we utilize the information of options volatility smirk between $t-14$ and $t-8$ to forecast earnings surprises on day $t$, there is slightly weaker evidence for $\text{SKEW}_{\text{lag}}$ to negatively covariate with the unexpected earnings as shown in Column 4–6.

#### *4.3.1. Market mechanism and predictability power of implied volatility smirk on unexpected earnings*

Table 5 examines whether there is a systematic difference in the predictive power of implied volatility smirk for unexpected earnings between the NYSE- and the NASDAQ-listed stocks. Controlling for an array of factors, suggested by Easley et al. (1998), that might increase the likelihood of informed trading in the options market and thus forecast the unexpected earnings released in announcements, we run the regression similar to Eq(3) but allow for different coefficients on the same variable respectively for NYSE stocks vs. Nasdaq stocks. We report in Table 5 the coefficients estimates from the same regression in separate two columns labeled "NYSE" and "NASDAQ" for each of three estimation methods.

We first note in Panel A that the coefficient estimates on SKEW are all negative regardless of the stock exchanges. However, the coefficient estimates on SKEW for NASDAQ stocks are always statistically significant in all three model specifications, but those for NYSE stocks are only statistically significant in the pooled cross section model. We then then perform the linear restriction test on the equality of coefficients on SKEW between NYSE and NASDAQ stocks for the pooled cross section model and the fixed effect panel model. The $F$ test statistics are both significantly reject the null of equality at 1% significance level. In terms of magnitude, the same degree of increase in the implied volatility smirk one week before the announcement day can predict a negative change on average in earnings surprises for a NASDAQ stock 3 times stronger than for a NYSE stock, *ceteris paribus*. For the Fama-MacBeth model, we report the mean comparison test for two time series of coefficient estimates on SKEW between NYSE stocks and NADAQ stocks. The corresponding $t$-statistic significantly rejects the null of equal predictability power of implied volatility smirk on unexpected earnings across exchanges. We obtain consistently similar results in Panel B when $\text{SKEW}_{\text{lag}}$ is used.

Insert Table 5 about here.

These results are consistent with our hypothesis H2. Options trading for the NASDAQ stocks is more informative about the upcoming, unreleased firm's earnings news than the options trading for the NYSE stocks. Is it because options traders on NASDAQ stocks are smarter than those who trade options on NYSE stocks, **or** options traders know more about NASDAQ stocks' unannounced earnings than they know about NYSE stocks' (information leakage), **or** even if options traders have the same information advantage for NASDAQ and NYSE stocks but they prefer to trade this information on options of NASDAQ stocks rather than trade it on options of NYSE stocks (regulatory arbitrage), and why? Both of two latter explanations ultimately point to the underlying institutional or regulatory differentials in the corporate governance, information disclosure or supervision and enforcement between two exchange. A recent paper by Suk and Frieder finds greater price responses to unexpected future earning information in NYSE than in NASDAQ, which implies that earnings surprises are relatively "unsurprising" for NASDAQ firms for which informed traders have anticipated the surprises and thus already traded in stock market.[8] Nevertheless we find the informed had also traded in options market to exploit their advantage.

### *4.3.2. The impact of SOX on the predictability power of implied volatility smirk on unexpected earnings*

To eliminate the unfair information advantage to selected investors, the U.S. regulators introduced a number of legislature measures that intended to level the ground for all

[8]SSRN971107 "Trading venue and voluntary earnings disclosure: the NYSE specialist market versus the NASDAQ dealer market"

investors either through more equal sharing of the corporate information in Reg FD or through more severe penalty on the misconduct of corporate executives in Sarbanes-Oxley Act. If selective disclosure of corporate information was effectively restricted by Reg FD after 2001, we should expect more transparent, frequent, and timely communications between public traded firms and investors tremendously reduce the information advantage for those options traders who had exploited their opportunistic edge before earnings announcements in the options market. Therefore the informative content extracted from options trading would be less significant to predict the upcoming earnings surprises, either the analysts had adjusted their earnings expectations or options traders at large bet along with the informed which dampen the implied volatility smirk measures. We expect to observe less significant or weaker predictive power of SKEW to earnings surprises after the Reg FD than before. On the other hand, after the passage of Sarbanes-Oxley Act, all investors, including those informed, faced more comprehensive scrutinies than ever on their trading activities before certain corporate events releasing any material information. The incentive to exploit the information advantage now compromised with the increased but differential severity of penalties across markets and varying likelihood of being caught in trading different types of securities. We would therefore expect informed investors trade more of their privately attained information in options market than before the legislature was enacted, because, in comparison to the stock market, suspicious options trading activities only recently started drawing public's attention and regulator's extensive investigations. After Sarbanes-Oxley Act, regulatory arbitrage between the stock and the options market encouraged informed traders to keep their hands clean in the former while migrating into the latter to continue their old games. It is an empirical question which story is dominant.

We split our sample into two subperiods, before and after 2002, corresponding to the pre- and post-SOX era. Table 6 examines whether the passage of SOX has affected the predictability power of implied volatility smirk on unexpected earnings and in which direction. To save space, we report only the results when SKEW is used to measure implied volatility smirk. The results on $\text{SKEW}_{\text{lag}}$ are similar and are available upon request. We adopt the estimation strategy similar to section 4.3.1 and test the equality of coefficients on SKEW for two subsamples of observations.

Insert Table 6 about here.

In the per-SOX era, the estimated coefficients on SKEW are negative but not statistically significant at conventional levels. The results are consistent across all three model specifications. In the post-SOX era, we observe significantly negative coefficient estimates on SKEW, whose magnitudes are also much greater than the estimates from the pre-SOX era, across all three model specifications. Test statistics show that the differences in estimated coefficients between the pre- and post-SOX eras are negatively large enough to reject the hypothesis that the predictability power of implied volatility smirk on unexpected earnings are constant or diminishing after the Sarbanes-Oxley Act was enacted in 2002.

These results are in favor of the "crowding-out" effect we conjectured above. Due to more severe penalty on corporate insiders' misconduct and stricter monitoring of stock trading activities, investors with advantageous private information about corporate earnings news opted was crowded out of the stock market and opted to trade more their information more in the options market. In another word, when the overall regulatory environment became more dangerous to make fast money in actually both the stock market and the options market, the de facto regulatory differentials between the stock and options market may have incentivized the informed to trade more in the relatively safer place, the options market.

### *4.4. Does implied volatility smirk predict stock returns following an earnings announcement?*

Table 7 reports test results on the predictability power of implied volatility smirk on cumulative abnormal returns following an earnings announcement. We examine the post-announcement abnormal returns over four different horizons: $\mathrm{CAR}[0, 1]$ captures the two-days abnormal return on the event day 0 and day 1 after the event; $\mathrm{CAR}[1, 39]$ and $\mathrm{CAR}[2, 40]$ correspond to short-term post-announcement abnormal returns over day 1 to day 39 and day 2 to 40, respectively; $\mathrm{CAR}[2, 60]$ represents the long-term abnormal return after the announcement over the period $[t + 2, t + 60]$, where $t$ denotes the date of earnings announcement. Except for those factors we previously included to explain the unexpected earnings, we also incorporate the unexpected earnings itself in the regression model to forecast the subsequent market reactions to the already-released corporate news.

Insert Table 7 about here.

We notice in Panel A through D that the estimated coefficients on SKEW across all four horizons remain significantly negative at least at 10% regardless of the model specifications. For example, the estimated coefficient on SKEW in the pooled OLS model is $-0.0256$ when $\text{CAR}[0, 1]$ is the dependent variable. We also observe an increasing magnitude of the estimated coefficient on SKEW with the increase in the horizon of abnormal returns. Using the results from the pooled OLS as an example, the estimated coefficient increases from $-0.0256$ to $-0.0534$ and to $-0.0997$ when dependent variable is CAR[0,1], CAR[2,40], and CAR[2,60], respectively. The increasing magnitude indicates the increasing marginal impact of SKEW on the cumulative abnormal returns. The results on the other two model specifications are similar. The increasing marginal impact persists when $\text{SKEW}_{\text{lag}}$ is used to measure implied volatility smirk, but statistically weaker.

More strikingly, we document a diminishing impact of SUE on CARs as the return horizon increases. Using the results from the pooled OLS as an example, the estimated coefficients on SKEW gradually decrease from 0.4501 when CAR[0,1] is the dependent variable to 0.1399 when CAR[2,60] is used. Moreover, the statistically significance of the estimated coefficient on SKEW almost disappears when CAR[2,60] is the dependent variable, a striking contrast compared to the results when CAR[0,1] is the dependent variable.

## 5. Conclusion

The instances of SEC enforcement in the options market is far fewer than those in the equity markets, although financial media has reported several cases of alleged insider trading in the options markets. Also, there is a lack of understanding on whether information extracted from the options market can predict important corporate announcements and actions. In this paper, we investigates whether information extracted from trading activities in the equity options markets can be used to forecast unexpected earnings.

Employing a sample of all firm quarterly earnings between 1996 and 2012, we document strong evidence that implied volatility smirk in the options markets does forecast unexpected earnings. Unexpected earnings is measured by the difference between analysts' expectations and IBES reported actual earnings, scaled by the standard deviation analyst forecasts, and implied volatility smirk is measured by the difference between the implied volatilities of OTM puts and ATM calls.

Furthermore, we document that the predicability is stronger for NASDAQ firms than for NYSE firms and is stronger over the post-SOX period than over the pre-SOX period. Moreover, we document that implied volatility smirk predicts both short- and long-term cumulative abnormal returns following an earnings announcement.

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Table 1: Summary statistics of unexpected earnings, implied volatility smirk, and cumulative abnormal returns

This table reports the summary statistics of earnings surprises, implied volatility smirk, and cumulative abnormal returns, as well as their correlations. SKEW, the measure of implied volatility smirk, is the difference between the implied volatilities of OTM puts and ATM calls. We lag SKEW by one week to get $\text{SKEW}_{\text{lag}}$. $\text{SKEW}^{\text{vw}}$ is volume-weighted volatility skew measure, where we use options trading volumes as weights to compute the average implied volatilities for OTM puts and ATM calls. SKEW and $\text{SKEW}^{\text{vw}}$ are calculated during a window of $t-7$ and $t-1$, where $t$ denotes the earnings announcement date. $\text{SKEW}_{\text{lag}}$ is calculated during a window of $t-14$ and $t-8$. We measure unexpected earnings using two commonly used definitions of standardized unexpected earnings (SUEs) (Livnat and Mendenhall, 2006). Both $\text{SUE}_1$ are $\text{SUE}_2$ are calculated as the difference between a measure of analysts' expectations and IBES reported actual earnings, scaled by the standard deviation analyst forecasts. In $\text{SUE}_1$ and $\text{SUE}_2$, we measure the analysts' expectations using the median and mean, respectively, of latest individual analysts forecasts issued within the 90 days prior to the EAD. The cumulative abnormal returns, $\text{CAR}[x, y]$, are the sum of characteristic risk-adjusted abnormal returns accumulating from $t+x$ to $t+y$, where $t$ denotes the earnings announcement date. To perform size and book-to-market ratio risk adjustment, we follow the procedure laid out at Professor Kenneth French's web site. Statistical significance level at 1% or lower is denoted by *.

Panel A: Univariate analysis

| Variable | N | Mean | STD | Skewness | Kurtosis | 25% | Median | 75% |
|---|---|---|---|---|---|---|---|---|
| SKEW | 81,244 | 0.0307 | 0.0433 | 4.5140 | 101.02 | 0.0136 | 0.0262 | 0.0424 |
| $\text{SKEW}_{\text{lag}}$ | 78,630 | 0.0309 | 0.0423 | 4.5174 | 91.42 | 0.0140 | 0.0265 | 0.0426 |
| $\text{SKEW}_{\text{vw}}$ | 43,909 | 0.0348 | 0.0416 | 4.4382 | 73.82 | 0.0177 | 0.0307 | 0.0457 |
| $\text{SKEW}^{\text{vw}}_{\text{lag}}$ | 42,185 | 0.0353 | 0.0427 | 4.3322 | 77.92 | 0.0184 | 0.0313 | 0.0460 |
| $\text{SUE}_1$ | 90,193 | 0.0001 | 0.0216 | -40.0130 | 4030.43 | 0.0000 | 0.0004 | 0.0016 |
| $\text{SUE}_2$ | 90,193 | 0.0001 | 0.0213 | -34.8160 | 3598.17 | -0.0002 | 0.0004 | 0.0016 |
| $\text{CAR}[0, 1]$ | 97,960 | 0.0004 | 0.0808 | -0.3309 | 9.41 | -0.0336 | 0.0000 | 0.0374 |
| $\text{CAR}[2, 40]$ | 94,170 | -0.0039 | 0.1660 | -0.3500 | 11.19 | -0.0794 | -0.0002 | 0.0774 |
| $\text{CAR}[2, 60]$ | 94,170 | -0.0068 | 0.2031 | -0.4101 | 10.29 | -0.0990 | -0.0017 | 0.0941 |

Panel B: Correlation coefficients

| Variable | $\text{SKEW}_{\text{lag}}$ | $\text{SKEW}_{\text{vw}}$ | $\text{SKEW}^{\text{vw}}_{\text{lag}}$ | $\text{SUE}_1$ | $\text{SUE}_2$ | $\text{CAR}[0, 1]$ | $\text{CAR}[2, 40]$ | $\text{CAR}[2, 60]$ |
|---|---|---|---|---|---|---|---|---|
| SKEW | 0.8304* | 0.7495* | 0.6978* | -0.0337* | -0.0298* | -0.0177* | -0.0210* | -0.0290* |
| $\text{SKEW}_{\text{lag}}$ | | 0.6864* | 0.7628* | -0.0239* | -0.0205* | -0.0148* | -0.0230* | -0.0279* |
| $\text{SKEW}_{\text{vw}}$ | | | 0.8267* | -0.0504* | -0.0458* | -0.0153* | -0.0362* | -0.0512* |
| $\text{SKEW}^{\text{vw}}_{\text{lag}}$ | | | | -0.0398* | -0.0357* | -0.0037 | -0.0381* | -0.0442* |
| $\text{SUE}_1$ | | | | | 0.9913* | 0.0861* | 0.0174* | 0.0090* |
| $\text{SUE}_2$ | | | | | | 0.0871* | 0.0177* | 0.0095* |
| $\text{CAR}[0, 1]$ | | | | | | | 0.0267* | 0.0256* |
| $\text{CAR}[2, 40]$ | | | | | | | | 0.7870* |

Table 2: Distribution of unexpected earnings and stock returns portfolios sorted on implied volatility smirk

This table presents unexpected earnings and cumulative abnormal returns of quintile portfolios sorted on implied volatility smirk, which are measured by SKEW, $\text{SKEW}_{\text{lag}}$ and $\text{SKEW}_{\text{vw}}$. For each calendar quarter between 1996:Q1 and 2012:Q4, we sort stocks into quintile portfolios by ranking firms based on their implied volatility smirks in the current quarter. SKEW, the measure of implied volatility smirk, is the difference between the implied volatilities of OTM puts and ATM calls. We lag SKEW by one week to get $\text{SKEW}_{\text{lag}}$. $\text{SKEW}^{\text{vw}}$ is volume-weighted volatility skew measure, where we use options trading volumes as weights to compute the average implied volatilities for OTM puts and ATM calls. SKEW and $\text{SKEW}^{\text{vw}}$ are calculated during a window of $t-7$ and $t-1$, where $t$ denotes the earnings announcement date. $\text{SKEW}_{\text{lag}}$ is calculated during a window of $t-14$ and $t-8$. Both $\text{SUE}_1$ are $\text{SUE}_2$ are calculated as the difference between a measure of analysts' expectations and IBES reported actual earnings, scaled by the standard deviation analyst forecasts. In $\text{SUE}_1$ and $\text{SUE}_2$, we measure the analysts' expectations using the median and mean, respectively, of latest individual analysts forecasts issued within the 90 days prior to the EAD. The cumulative abnormal returns, $\text{CAR}[x, y]$, are the sum of characteristic risk-adjusted abnormal returns accumulating from $t+x$ to $t+y$, where $t$ denotes the earnings announcement date. Statistical significance level at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | $Q_1 - Q_5$ |
|---|---|---|---|---|---|---|
| Panel A: SKEW | | | | | | |
| $\text{SUE}_1$ $(10^{-2})$ | 0.0551 | 0.0694 | 0.0673 | 0.0563 | -0.0095 | 0.0646*** |
| $\text{SUE}_2$ $(10^{-2})$ | 0.0503 | 0.0656 | 0.0672 | 0.0529 | -0.0086 | 0.0589** |
| $\text{CAR}[0, 1]$ (%) | 0.2078 | 0.1844 | 0.1194 | 0.1815 | -0.279 | 0.4868*** |
| $\text{CAR}[2, 40]$ (%) | -0.2856 | -0.3871 | -0.3199 | -0.3785 | -0.8368 | 0.5513* |
| $\text{CAR}[2, 60]$ (%) | -0.5435 | -0.5584 | -0.5755 | -0.7564 | -1.4882 | 0.9447** |
| Panel B: $\text{SKEW}_{\text{lag}}$ | | | | | | |
| $\text{SUE}_1$ $(10^{-2})$ | 0.0598 | 0.0711 | 0.0574 | 0.0577 | -0.013 | 0.0728*** |
| $\text{SUE}_2$ $(10^{-2})$ | 0.0575 | 0.0654 | 0.0567 | 0.0562 | -0.0141 | 0.0716*** |
| $\text{CAR}[0, 1]$ (%) | 0.183 | 0.1346 | 0.1703 | 0.1457 | -0.1645 | 0.3475*** |
| $\text{CAR}[2, 40]$ (%) | -0.4333 | -0.3259 | -0.2976 | -0.4437 | -0.8958 | 0.4625* |
| $\text{CAR}[2, 60]$ (%) | -0.7933 | -0.5487 | -0.5713 | -0.6395 | -1.4679 | 0.6746** |
| Panel C: $\text{SKEW}_{\text{vw}}$ | | | | | | |
| $\text{SUE}_1$ $(10^{-2})$ | 0.0478 | 0.074 | 0.0624 | 0.0648 | -0.0348 | 0.0826* |
| $\text{SUE}_2$ $(10^{-2})$ | 0.041 | 0.0733 | 0.0623 | 0.0623 | -0.0358 | 0.0768* |
| $\text{CAR}[0, 1]$ (%) | 0.1231 | 0.1121 | 0.1489 | 0.0635 | -0.2398 | 0.3629*** |
| $\text{CAR}[2, 40]$ (%) | -0.2961 | 0.0081 | 0.0223 | -0.1759 | -1.304 | 1.0079** |
| $\text{CAR}[2, 60]$ (%) | -0.2335 | 0.0285 | 0.0074 | -0.383 | -1.7779 | 1.5444*** |

Table 3: Distribution of unexpected earnings in portfolios sorted on both implied volatility smirk and firm characteristics

This table reports the distribution of unexpected earnings within characteristic- and SKEW-sorted quintile portfolios. Firm characteristics includes market beta (BETA), firm size (SIZE), market-to-book ratio (MB), compound short-term returns (RET1M), and idiosyncratic volatility (VAR). Here unexpected earnings are measured by the differences between IBES-reported analyst forecasts consensus and actual earnings, scaled by the dispersion of analyst forecasts ($SUE_1$). SKEW, the measure of implied volatility smirk, is the difference between the implied volatilities of OTM puts and ATM calls. We lag SKEW by one week to get $SKEW_{lag}$. SKEW is calculated during a window of $t-7$ and $t-1$, where $t$ denotes the earnings announcement date. $SKEW_{lag}$ is calculated during a window of $t-14$ and $t-8$. BETA measures the systematic risk, calculated from the standard market model. Unexpected earnings are measured by $SUE_2$, the differences between IBES-reported analyst forecasts consensus and actual earnings. SIZE is the market capitalization of a firm at the end of the month immediately prior to an earnings announcement date. RET1M is the compound gross return over [$t-1$ month, $t$], where $t$ is the date of earnings announcement. VAR is idiosyncratic return volatility calculated as the standard deviation of the residuals from the Fama-French (1993) model, following Ang et al. (2006). To calculate VAR, we require at least 15 trading days of non-missing returns data. Statistical significance level at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | SKEW | | | $SKEW_{lag}$ | | |
|---|---|---|---|---|---|---|
| | $Q_1$ | $Q_5$ | $Q_1-Q_5$ | $Q_1$ | $Q_5$ | $Q_1-Q_5$ |
| Panel A: BETA | | | | | | |
| $Q_1$ (smallest) | 0.0704 | -0.0298 | 0.1002*** | 0.0709 | -0.0027 | 0.0737*** |
| $Q_2$ | 0.0714 | -0.0183 | 0.0897*** | 0.0675 | -0.0275 | 0.0949*** |
| $Q_3$ | 0.0228 | -0.0144 | 0.0372 | 0.0498 | -0.0274 | 0.0773** |
| $Q_4$ | 0.0576 | -0.0047 | 0.0623** | 0.0674 | 0.0003 | 0.0672** |
| $Q_5$ (largest) | 0.0689 | -0.0101 | 0.0791 | 0.0971 | -0.0322 | 0.1293* |
| Panel B: SIZE | | | | | | |
| $Q_1$ (smallest) | 0.0438 | -0.0400 | 0.0838** | 0.0721 | -0.0515 | 0.1236*** |
| $Q_2$ | 0.0707 | 0.0218 | 0.0490* | 0.0566 | 0.0377 | 0.0189 |
| $Q_3$ | 0.0671 | 0.0241 | 0.0429* | 0.0941 | 0.0037 | 0.0905*** |
| $Q_4$ | 0.0589 | -0.0171 | 0.0760* | 0.0531 | 0.0152 | 0.0379 |
| $Q_5$ (largest) | 0.0292 | -0.0845** | 0.1138 | 0.0451 | -0.0797 | 0.1248** |
| Panel C: MB | | | | | | |
| $Q_1$ (smallest) | 0.0035 | -0.2298 | 0.2333** | 0.0875 | -0.1988 | 0.2862*** |
| $Q_2$ | 0.0635 | 0.0197 | 0.0439* | 0.0372 | 0.0197 | 0.0176 |
| $Q_3$ | 0.0851 | 0.0315 | 0.0536*** | 0.0816 | 0.0240 | 0.0575*** |
| $Q_4$ | 0.0660 | 0.0620 | 0.0040 | 0.0553 | 0.0667 | -0.0114 |
| $Q_5$ (largest) | 0.0592 | 0.0702 | -0.0110 | 0.0755 | 0.0362 | 0.0394** |
| Panel D: RET1M | | | | | | |
| $Q_1$ (smallest) | 0.0111 | -0.1105 | 0.1216** | 0.0417 | -0.1063 | 0.1480** |
| $Q_2$ | 0.0576 | -0.0001 | 0.0578** | 0.0697 | -0.0100 | 0.0797*** |
| $Q_3$ | 0.0783 | -0.0243 | 0.1026** | 0.0669 | -0.0250 | 0.0919* |
| $Q_4$ | 0.0457 | 0.0235 | 0.0222 | 0.0796 | 0.0150 | 0.0646** |
| $Q_5$ (largest) | 0.0909 | 0.0408 | 0.0502** | 0.0658 | 0.0442 | 0.0216 |
| Panel E: VAR | | | | | | |
| $Q_1$ (smallest) | 0.0332 | 0.0045 | 0.0287 | 0.0364 | 0.0281 | 0.0083 |
| $Q_2$ | 0.0589 | 0.0191 | 0.0397*** | 0.0626 | 0.0259 | 0.0367** |
| $Q_3$ | 0.0658 | -0.0598 | 0.1257*** | 0.0791 | -0.0553 | 0.1344*** |
| $Q_4$ | 0.0751 | -0.0197 | 0.0948** | 0.0775 | -0.0008 | 0.0783*** |
| $Q_5$ (largest) | 0.0554 | -0.0515 | 0.1069* | 0.0599 | -0.1063 | 0.1662** |

Table 4: Does implied volatility smirk predict unexpected earnings?

This table reports the estimated regression coefficients of the OLS regression (Models 1 and 4), fixed effects (Models 2 and 5), and Fama-MacBeth two-stage regression models (Models 3 and 6), respectively. The dependent variable is unexpected earnings, measured by the differences between IBES-reported analyst forecasts consensus and actual earnings, scaled by the dispersion of analyst forecasts ($SUE_1$). SKEW, the measure of implied volatility smirk, is the difference between the implied volatilities of OTM puts and ATM calls. We lag SKEW by one week to get $SKEW_{lag}$. SKEW is calculated during a window of $t-7$ and $t-1$, where $t$ denotes the earnings announcement date. $SKEW_{lag}$ is calculated during a window of $t-14$ and $t-8$. RET1M and RET3M are the compound gross returns over $[t-1, t]$ and $[t-3, t]$ months, respectively, where $t$ is the date of earnings announcement. BETA measures the systematic risk, calculated from the standard market model. VAR is idiosyncratic return volatility calculated as the standard deviation of the residuals from the Fama-French (1993) model, following Ang et al. (2006). To calculate VAR, we require at least 15 trading days of non-missing returns data. Book-to-market equity (MB) is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. SIZE is the logged value of the product of monthly closing price and the number of outstanding shares in June. SPR is the bid-ask spread calculated from CRSP, following Chung and Zhang (2013). SUV is the standardized unexplained volume from Garfinkel (2009). DTO is the market-adjusted turnover de-trended by its 180 trading day median, following Garfinkel (2009) and Anderson and Dyl (2005). Standard errors are reported in brackets. Statistical significance level at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Pooled Cross Section | Panel Fixed Effects | Fama-MacBeth Two Stage | Pooled Cross Section | Panel Fixed Effects | Fama-MacBeth Two Stage |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| SKEW | -0.0138** | -0.0114*** | -0.0116*** | | | |
| | [0.0067] | [0.0016] | [0.0035] | | | |
| $SKEW_{lag}$ | | | | -0.0092 | -0.0063*** | -0.0063* |
| | | | | [0.0068] | [0.0017] | [0.0033] |
| RET1M | -0.0013 | -0.0012** | -0.0007 | -0.0011 | -0.0010* | -0.0003 |
| | [0.0010] | [0.0005] | [0.0010] | [0.0010] | [0.0005] | [0.0011] |
| RET3M | 0.0019*** | 0.0017*** | 0.0019*** | 0.0021*** | 0.0018*** | 0.0021*** |
| | [0.0004] | [0.0003] | [0.0005] | [0.0004] | [0.0003] | [0.0006] |
| BETA | 0.0002* | 0.0001 | 0.0002 | 0.0002** | 0.0002* | 0.0002 |
| | [0.0001] | [0.0001] | [0.0002] | [0.0001] | [0.0001] | [0.0002] |
| VAR | -0.0054 | -0.0113*** | -0.0013 | -0.0071 | -0.0143*** | -0.0007 |
| | [0.0056] | [0.0020] | [0.0035] | [0.0057] | [0.0020] | [0.0035] |
| MB | 0.0002 | 0.0007*** | 0.0001 | 0.0002 | 0.0006*** | 0.0002 |
| | [0.0002] | [0.0002] | [0.0001] | [0.0002] | [0.0002] | [0.0001] |
| SIZE | -0.0002* | -0.0006*** | -0.0002** | -0.0002 | -0.0006*** | -0.0002** |
| | [0.0001] | [0.0002] | [0.0001] | [0.0001] | [0.0002] | [0.0001] |
| SPR | -0.0064 | -0.0073 | -0.2946 | -0.0044 | -0.0062 | -0.4716 |
| | [0.0048] | [0.0098] | [0.2043] | [0.0047] | [0.0099] | [0.3118] |
| SUV | -0.0002* | -0.0003*** | -0.0001 | -0.0002* | -0.0003*** | -0.0001 |
| | [0.0001] | [0.0001] | [0.0001] | [0.0001] | [0.0001] | [0.0001] |
| DTO | 0.1072 | 0.1189*** | 0.0222 | 0.105 | 0.1198*** | 0.02 |
| | [0.0825] | [0.0083] | [0.0200] | [0.0850] | [0.0084] | [0.0189] |
| $D_{Industry}$ | yes | yes | yes | yes | yes | yes |
| $D_{Exchange}$ | yes | yes | yes | yes | yes | yes |
| $D_{Year, Month}$ | yes | yes | no | yes | yes | no |
| $R^2(\%)$ | 0.82 | 0.39 | 18.02 | 0.76 | 0.37 | 17.99 |
| Nobs | 72,289 | 72,289 | 72,289 | 69,995 | 69,995 | 69,995 |
| $F$-stat | 7.263*** | 9.998*** | 2.487*** | 7.101*** | 9.407*** | 1.864** |

Table 5: Are the linkage between implied volatility smirk and unexpected earnings different for stocks listed on NYSE and NASDAQ?

This table reports the estimated regression coefficients, separately for stocks listed on NYSE and NASDAQ, of the OLS regression, fixed effects, and Fama-MacBeth regression models, respectively. The dependent variable is unexpected earnings, measured by the differences between IBES-reported analyst forecasts consensus and actual earnings ($SUE_1$). Panel A (B) reports the results using SKEW and $SKEW_{lag}$ as the measure of implied volatility smirk, respectively. Standard errors are reported in brackets. Statistical significance level at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Panel A: SKEW as the measure of implied volatility smirk

| | Pooled Cross Section | | Panel Fixed Effects | | Fama-MacBeth Two Stage | |
|---|---|---|---|---|---|---|
| | NYSE | NASDAQ | NYSE | NASDAQ | NYSE | NASDAQ |
| SKEW | -0.0144*** | -0.0383*** | -0.0109 | -0.0316*** | -0.0173 | -0.0339*** |
| | [0.0043] | [0.0039] | [0.0162] | [0.0107] | [0.0133] | [0.0110] |
| | $F$-stat = 17.114*** | | $F$-stat = 9.266*** | | $t$-stat = 7.678*** | |
| RET1M | 0.0321 | -0.0175 | 0.0544 | -0.026 | 0.1107* | 0.0011 |
| | [0.0391] | [0.0298] | [0.0728] | [0.0414] | [0.0643] | [0.0475] |
| RET3M | 0.1340*** | 0.0623*** | 0.1093*** | 0.0451** | 0.2183*** | 0.1370*** |
| | [0.0197] | [0.0139] | [0.0330] | [0.0188] | [0.0433] | [0.0252] |
| BETA | 0.0153*** | 0.0034 | -0.0044 | 0.0054 | 0.0212** | 0.0000 |
| | [0.0059] | [0.0047] | [0.0123] | [0.0077] | [0.0106] | [0.0070] |
| VAR | -0.2804** | 0.1079 | -0.6200 | 0.1019 | -0.1794 | 0.1195 |
| | [0.1153] | [0.0717] | [0.4979] | [0.1247] | [0.3360] | [0.1272] |
| BM | -0.0001 | -0.0007 | 0.0001 | 0.0001 | -0.001 | -0.0008 |
| | [0.0002] | [0.0007] | [0.0001] | [0.0007] | [0.0010] | [0.0011] |
| SIZE | -0.0183*** | -0.0078 | -0.0623*** | -0.0681*** | -0.0187*** | -0.0096 |
| | [0.0043] | [0.0058] | [0.0239] | [0.0159] | [0.0069] | [0.0085] |
| SPR | -1.0505** | -0.6879 | -0.7448* | 0.3007 | -9.8379 | -13.874 |
| | [0.4834] | [1.4375] | [0.4427] | [1.8628] | [8.2829] | [10.6078] |
| SUV | -0.0171*** | 0.0028 | -0.0176* | 0.0022 | -0.0118** | -0.0025 |
| | [0.0031] | [0.0026] | [0.0092] | [0.0038] | [0.0059] | [0.0056] |
| DTO | 5.7519*** | 0.3913 | 5.2643 | 0.1361 | 1.033 | 0.2225 |
| | [0.5716] | [0.4674] | [5.3973] | [0.6248] | [1.6813] | [0.9916] |
| $D_{\text{Industry}}$ | yes | yes | yes | yes | yes | yes |
| $D_{\text{Year, Month}}$ | yes | yes | yes | yes | no | no |
| $R^2$ (%) | 0.71 | 0.71 | 0.61 | 0.73 | 8.51 | 6.83 |
| Nobs | 44,210 | 27,882 | 44,210 | 27,882 | 44,210 | 27,882 |
| $F$-stat | 6.98*** | 4.398*** | 4.298*** | 4.507*** | 2.787*** | 2.595*** |

Table 5 (Cont'd)

Panel B: Lagged SKEW as the measure of implied volatility smirk

| | Pooled Cross Section | | Panel Fixed Effects | | Fama-MacBeth Two Stage | |
|---|---|---|---|---|---|---|
| | NYSE | NASDAQ | NYSE | NASDAQ | NYSE | NASDAQ |
| $SKEW_{lag}$ | -0.0160*** | -0.0273*** | -0.0159 | -0.0109 | -0.018 | -0.0247*** |
| | [0.0043] | [0.0040] | [0.0170] | [0.0140] | [0.0129] | [0.0081] |
| | $F$-stat =3.6495* | | $F$-stat = 0.8848 | | $t$-stat = 3.5032*** | |
| RET1M | 0.0307 | -0.0347 | 0.0682 | -0.0415 | 0.0893 | -0.0305 |
| | [0.0395] | [0.0305] | [0.0628] | [0.0413] | [0.0597] | [0.0494] |
| RET3M | 0.1416*** | 0.0716*** | 0.1137*** | 0.0533*** | 0.2320*** | 0.1603*** |
| | [0.0199] | [0.0142] | [0.0347] | [0.0196] | [0.0425] | [0.0280] |
| BETA | 0.0188*** | 0.001 | 0.0028 | 0.0052 | 0.0216** | -0.0004 |
| | [0.0059] | [0.0048] | [0.0132] | [0.0079] | [0.0105] | [0.0068] |
| VAR | -0.3955*** | 0.0847 | -0.8514* | 0.0708 | -0.2455 | 0.1168 |
| | [0.1159] | [0.0741] | [0.5090] | [0.1366] | [0.3442] | [0.1285] |
| BM | -0.0001 | -0.0004 | 0.0001 | 0.0004 | -0.0012 | -0.0007 |
| | [0.0002] | [0.0007] | [0.0001] | [0.0007] | [0.0009] | [0.0011] |
| SIZE | -0.0223*** | -0.0064 | -0.0770*** | -0.0635*** | -0.0225*** | -0.0108 |
| | [0.0044] | [0.0060] | [0.0242] | [0.0152] | [0.0063] | [0.0076] |
| SPR | -0.7571 | -0.33 | -0.6076 | 0.3531 | -10.0952 | -20.9079 |
| | [0.4890] | [1.4762] | [0.4456] | [1.9848] | [8.7074] | [15.8708] |
| SUV | -0.0193*** | -0.0016 | -0.0193** | -0.0025 | -0.0144** | -0.0022 |
| | [0.0031] | [0.0029] | [0.0090] | [0.0037] | [0.0061] | [0.0054] |
| DTO | 5.6007*** | 0.067 | 5.2554 | -0.0127 | 0.561 | 0.1518 |
| | [0.5732] | [0.4699] | [5.5586] | [0.6538] | [1.8792] | [0.9002] |
| $D_{Industry}$ | yes | yes | yes | yes | yes | yes |
| $D_{Year,\ Month}$ | yes | yes | yes | yes | no | no |
| $R^2$ (%) | 0.76 | 0.55 | 0.69 | 0.47 | 8.66 | 7.01 |
| Nobs | 42,866 | 26,935 | 42,866 | 26,935 | 42,866 | 26,935 |
| $F$-stat | 7.2524*** | 3.3335*** | 4.7975*** | 4.3762*** | 3.7237*** | 2.5924*** |

Table 6: Are the linkage between implied volatility smirk and unexpected earnings different over the pre- and post-SOX eras?

This table reports the estimated regression coefficients, separately for the pre- and post-SOX eras, of the OLS regression, fixed effects, and Fama-MacBeth regression models, respectively. The dependent variable is unexpected earnings, measured by the differences between IBES-reported analyst forecasts consensus and actual earnings ($SUE_1$). Standard errors are reported in brackets. Statistical significance level at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Pooled Cross Section | | Panel Fixed Effect | | Fama-MacBeth Two Stage | |
|---|---|---|---|---|---|---|
| | Pre-SOX | Post-SOX | Pre-SOX | Post-SOX | Pre-SOX | Post-SOX |
| SKEW | -0.0013 | -0.0431*** | -0.0009 | -0.0353*** | -0.0034 | -0.0443*** |
| | [0.0080] | [0.0166] | [0.0043] | [0.0046] | [0.0081] | [0.0134] |
| | $F$-stat =5.256** | | $F$-stat = 30.267*** | | $t$-stat = 7.678*** | |
| RET1M | -0.0183 | 0.0285 | -0.0168 | 0.044 | 0.0267 | 0.0407 |
| | [0.0315] | [0.0722] | [0.0280] | [0.0408] | [0.0394] | [0.0615] |
| RET3M | 0.0678*** | 0.1056*** | 0.0485*** | 0.0748*** | 0.1476*** | 0.1836*** |
| | [0.0145] | [0.0275] | [0.0140] | [0.0189] | [0.0346] | [0.0385] |
| BETA | 0.0106 | 0.0084 | -0.0012 | 0.0058 | 0.0118 | 0.0112 |
| | [0.0066] | [0.0064] | [0.0083] | [0.0075] | [0.0074] | [0.0088] |
| VAR | 0.0804 | -0.0769 | 0.3118* | -0.3859*** | 0.0628 | -0.0258 |
| | [0.0955] | [0.2562] | [0.1776] | [0.1412] | [0.1417] | [0.2347] |
| BM | -0.0001 | -0.0004 | 0.0001 | -0.0005 | -0.0002 | -0.0004 |
| | [0.0001] | [0.0004] | [0.0002] | [0.0008] | [0.0009] | [0.0008] |
| SIZE | -0.0209*** | -0.0117* | -0.1010*** | -0.0356** | -0.0198*** | -0.0144 |
| | [0.0046] | [0.0063] | [0.0133] | [0.0155] | [0.0039] | [0.0094] |
| SPR | -1.3422*** | -2.7676 | -0.8025* | -2.1192 | -1.1718* | -19.2494 |
| | [0.4519] | [2.1463] | [0.4376] | [1.9620] | [0.6302] | [17.1215] |
| SUV | -0.0037 | -0.0063 | -0.0042 | -0.0107*** | -0.0089 | -0.0027 |
| | [0.0075] | [0.0041] | [0.0036] | [0.0033] | [0.0069] | [0.0056] |
| DTO | 1.3904 | 3.4305 | -0.094 | 3.7132*** | 1.8379 | 0.4544 |
| | [1.2264] | [2.9362] | [0.5670] | [0.5146] | [1.2005] | [1.1408] |
| $D_{\text{Industry}}$ | yes | yes | yes | yes | yes | yes |
| $D_{\text{Year, Month}}$ | yes | yes | yes | yes | no | no |
| $R^2$ (%) | 0.61 | 0.82 | 0.14 | 0.11 | 3.75 | 6.33 |
| Nobs | 28,037 | 44,055 | 28,037 | 44,055 | 28,037 | 44,055 |
| $F$-stat | 5.657*** | 4.544*** | 4.449*** | 5.227*** | 5.747*** | 2.425** |

Table 7: Does implied volatility smirk predict cumulative abnormal returns?

This table reports the estimated regression coefficients. The dependent variable are CAR$[x, y]$, the sum of characteristic risk-adjusted cumulative abnormal returns between $t + x$ to $t + y$, where $t$ denotes the earnings announcement date. Panel A, B, C, and D reports the results on CAR$[0, 1]$, CAR[1,39], CAR$[2, 40]$, CAR$[2, 60]$, respectively. Model 1 (4), Model 2 (5), and Model 3 (6) report coefficient estimates of the OLS regression, fixed-effects, and Fama-MacBeth regression models, respectively. Standard errors are reported in brackets. Statistical significance level at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Pooled Cross Section | Panel Fixed Effects | Fama-MacBeth Two Stage | Pooled Cross Section | Panel Fixed Effects | Fama-MacBeth Two Stage |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: CAR$[0, 1]$ as the dependent variable | | | | | | |
| SKEW | -0.0256** | -0.0220* | -0.0402*** | | | |
| | [0.0102] | [0.0122] | [0.0100] | | | |
| $\text{SKEW}_{\text{lag}}$ | | | | -0.0139 | -0.0081 | -0.0195 |
| | | | | [0.0100] | [0.0119] | [0.0120] |
| SUE | 0.4501*** | 0.4345*** | 2.2173*** | 0.4500*** | 0.4349*** | 2.1643*** |
| | [0.0945] | [0.1260] | [0.2699] | [0.0984] | [0.1268] | [0.2482] |
| RET1M | 0.0049 | 0.0090** | 0.0087** | 0.0047 | 0.0099*** | 0.0092** |
| | [0.0035] | [0.0036] | [0.0043] | [0.0036] | [0.0037] | [0.0044] |
| RET3M | -0.0017 | -0.0075*** | -0.0080*** | -0.0013 | -0.0073*** | -0.0084*** |
| | [0.0018] | [0.0019] | [0.0025] | [0.0018] | [0.0019] | [0.0028] |
| BETA | 0.0003 | -0.0002 | 0.0011 | 0.0001 | -0.0003 | 0.0013 |
| | [0.0005] | [0.0007] | [0.0008] | [0.0005] | [0.0007] | [0.0009] |
| VAR | -0.0363*** | 0.0006 | -0.0455*** | -0.0378*** | 0.0025 | -0.0480*** |
| | [0.0079] | [0.0124] | [0.0101] | [0.0082] | [0.0123] | [0.0120] |
| BM | 0.0004 | 0.0025*** | 0.0008* | 0.0002 | 0.0019** | 0.0005 |
| | [0.0005] | [0.0009] | [0.0005] | [0.0005] | [0.0009] | [0.0005] |
| SIZE | -0.0003 | -0.0094*** | -0.0001 | -0.0003 | -0.0087*** | -0.0001 |
| | [0.0002] | [0.0008] | [0.0003] | [0.0002] | [0.0009] | [0.0003] |
| SPR | 0.0381 | 0.06 | 0.2138 | 0.0686 | 0.0942 | 0.3664 |
| | [0.0552] | [0.0595] | [0.2419] | [0.0569] | [0.0615] | [0.2590] |
| SUV | -0.0008*** | -0.0005 | -0.0005 | -0.0006* | -0.0003 | -0.0003 |
| | [0.0003] | [0.0003] | [0.0003] | [0.0003] | [0.0003] | [0.0003] |
| DTO | 0.1320* | 0.0973 | 0.1410** | 0.1590** | 0.1117 | 0.1711** |
| | [0.0736] | [0.0780] | [0.0609] | [0.0747] | [0.0797] | [0.0680] |
| $\text{D}_{\text{Industry}}$ | yes | yes | yes | yes | yes | yes |
| $\text{D}_{\text{Exchange}}$ | yes | yes | yes | yes | yes | yes |
| $\text{D}_{\text{Year, Month}}$ | yes | yes | no | yes | yes | no |
| $R^2(\%)$ | 1.03 | 1.23 | 5.10 | 1.02 | 1.21 | 5.13 |
| Nobs | 72,289 | 72,289 | 72,289 | 69,995 | 69,995 | 69,995 |
| $F$-stat | 3.252*** | 6.297*** | 6.336*** | 3.114*** | 5.914*** | 5.851*** |

Table 7 (Cont'd)

| | Pooled Cross Section | Panel Fixed Effects | Fama-MacBeth Two Stage | Pooled Cross Section | Panel Fixed Effects | Fama-MacBeth Two Stage |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel B: CAR[1, 39] as the dependent variable | | | | | | |
| SKEW | -0.0504** | -0.0502** | -0.0642** | | | |
| | [0.0207] | [0.0228] | [0.0246] | | | |
| $SKEW_{lag}$ | | | | -0.0484** | -0.0468* | -0.0503** |
| | | | | [0.0221] | [0.0240] | [0.0216] |
| SUE | 0.3838*** | 0.3540*** | 1.9502*** | 0.3869*** | 0.3567*** | 1.9612*** |
| | [0.1334] | [0.1150] | [0.2801] | [0.1404] | [0.1218] | [0.2967] |
| Panel C: CAR[2, 40] as the dependent variable | | | | | | |
| SKEW | -0.0534*** | -0.0543** | -0.0563** | | | |
| | [0.0198] | [0.0218] | [0.0222] | | | |
| $SKEW_{lag}$ | | | | -0.0403* | -0.0414* | -0.0363* |
| | | | | [0.0213] | [0.0230] | [0.0192] |
| SUE | 0.1575* | 0.1326** | 0.8014*** | 0.1675* | 0.1398** | 0.8300*** |
| | [0.0855] | [0.0646] | [0.2216] | [0.0907] | [0.0673] | [0.2319] |
| Panel D: CAR[2, 60] as the dependent variable | | | | | | |
| SKEW | -0.0997*** | -0.0927*** | -0.0866*** | | | |
| | [0.0235] | [0.0264] | [0.0263] | | | |
| $SKEW_{lag}$ | | | | -0.0703*** | -0.0628** | -0.0436* |
| | | | | [0.0251] | [0.0281] | [0.0239] |
| SUE | 0.1399 | 0.0773 | 0.9420*** | 0.1867* | 0.1168 | 1.0421*** |
| | [0.0991] | [0.0630] | [0.2922] | [0.1080] | [0.0724] | [0.2774] |