Chapter

Investors' Greed and Fear: An Event Study of Analyst Recommendations

Qingxia (Jenny) Wang

Abstract

We investigate the effect of the skewness developed by the CBOE, called SKEW, on investors' reactions to analyst recommendations. Our results show that the abnormal stock returns around analyst recommendation revisions are closely correlated with contemporaneous SKEW changes. Specifically, positive (negative) abnormal returns following analyst recommendation upgrades (downgrades) are stronger when daily SKEW increases (decreases). A potential explanation for this relation is that SKEW captures investors' greed (excitement) in the stock market. Similar to the CBOE VIX, SKEW might act as another measure to reflect investors' moods or sentiments. However, in contrast to VIX, which is usually used as investors' fear gauge, SKEW is the opposite of investors' fear, measuring investors' consensus view of future positive news. Furthermore, we show that the magnitudes of abnormal returns associated with the change in SKEW are larger for the NASDAQ than for the NYSE on recommendation announcement days. This may manifest the different types of firms listed on these two stock exchanges.

Keywords: analyst recommendation revision, abnormal return, investors' greed, investors' fear, SKEW, VIX

1. Introduction

Prior literature has extensively investigated the market volatility expectations, captured by the implied volatility index (VIX).[1] VIX is developed by the Chicago Board Options Exchange (CBOE), measuring investors' fear in the US stock market [1, 2]. Later, the CBOE developed another index, SKEW, to estimate the tail risk of the S&P 500 returns that are not fully captured by VIX. While empirical evidence documents that asymmetry measures outperform volatility measures in predicting market returns, studies on SKEW are scant and it is inconclusive on whether SKEW could be a fear or greed indicator. Using a similar procedure for constructing the CBOE SKEW, Elyasiani et al. [7] propose an Italian SKEW (ITSKEW). They argue that SKEW (CBOE SKEW or ITSKEW) acts as a measure of market greed (excitement), and has a

[1] For example, see [1–6].

significant contemporaneous relation with returns.[2] However, Mora-Valencia et al. [8] explain the SKEW index as a fear indicator. Liu and Faff [9] question the usefulness of SKEW as an indicator of institutional anxiety. Our study complements prior research by further examining the effect of SKEW on stock returns around corporate events. Specifically, we investigate how the change in SKEW around analyst recommendations is related to announcement returns.

Analyst recommendation revisions contain useful information for investment decisions. For example, Stickel [10] shows that brokerage analyst recommendations have a strong effect on short-term stock prices. Womack [11] provides evidence that there exist significant discrepancies between pre-recommendation prices and post-recommendation values. Barber et al. [12] document that investors can earn abnormal returns, both gross and net of trading costs, by taking advantage of analyst recommendations. Jegadeesh and Kim [13] provide international evidence from G7 countries to show that stock prices react significantly to analyst recommendation revisions. Jegadeesh and Kim [14] further document a stronger market reaction to recommendation revisions when the new recommendations move away from the consensus. Loh and Stulz [15] show that in bad times, recommendation revisions have a larger impact on stock prices.

In general, the literature finds that around analyst recommendations, upgrades are related to higher abnormal stock returns, whereas downgrades are associated with lower abnormal stock returns (normally negative abnormal stock returns). Based on stocks listed on the NYSE, Kliger and Kudryavtsev [16] explore the interaction between abnormal stock returns and volatility expectations around recommendation revisions. They use the CBOE VIX to capture investors' market volatility expectations, which is also known as the investors' fear gauge [1, 2]. Their results show that VIX changes are highly correlated with investors' sentiment by reporting that positive (negative) abnormal stock returns are stronger when the daily VIX decreases (increases) for recommendation upgrades (downgrades). In the spirit of Kliger and Kudryavtsev [16], we examine the effect of SKEW on investors' reaction to analyst recommendation revisions. Skewness demonstrates one type of behavior regarding investors' attitude toward risks. For example, Han [17] shows that model-free implied skewness (MFIS) is associated with investor sentiment in which several investor sentiment proxies are applied [18–20]. Green and Hwang [21] document that initial public offerings (IPOs) with high expected skewness achieve greater first-day returns. This might be explained as individuals' affinity for lotteries, reflected by higher skewness.

We examine stocks listed on the NYSE and the NASDAQ separately because, on these two stock exchanges, the types of listed firms and investors are potentially different [22–25] and the market responses to news announcements are also different [26, 27].[3] We further contrast the effect of the market SKEW on investors' responses to analyst recommendation revisions on these two stock exchanges.

For both the NYSE and the NASDAQ, we show that the abnormal returns before announcement days (day −1) and on the announcement days (day 0) are significantly higher when SKEW increases (i.e., ΔSKEW>0) than when SKEW

[2] For instance, the change in SKEW during time t is significantly related to stock returns during the same period.

[3] Investors might have a different perception of stocks listed on the NYSE and NASDAQ. For example, most firms that trade on the NASDAQ are the young, high technology, and innovative firms.

decreases (i.e., ΔSKEW < 0). For recommendation upgrades, the abnormal returns for these 2 days are generally positive[4] and are larger for ΔSKEW>0 than for ΔSKEW < 0. Accordingly, for recommendation downgrades, the abnormal returns for these 2 days are generally negative[5]. Moreover, the magnitudes of abnormal returns for ΔSKEW>0 are significantly less than that for ΔSKEW < 0. That is, abnormal returns are more negative on both days when SKEW decreases than SKEW increases. We argue that these results are analogous to investors' preference for stocks with lottery features [20, 28].

Furthermore, we show that on recommendation revision days (i.e., day 0), the magnitudes of corresponding abnormal returns are larger for stocks listed on the NASDAQ than those listed on the NYSE, that is, abnormal returns are more positive (negative) for upgrades (downgrades). This could be explained by the high volatility of high-tech stocks listed on the NASDAQ, which contributes to higher (lower) abnormal returns for upgrades (downgrades).

Overall, we observe a positive relationship between the changes in SKEW and abnormal returns around recommendation revisions. As such, we propose that SKEW is an indicator of investors' greed measure rather than a fear gauge. This is consistent with the study of Green and Hwang [21] and Elyasiani et al. [7].

Our study contributes to the literature on psychological bias and investors' decision-making in financial markets around news announcements. Through the corporate news events (i.e., analyst recommendations), we show that the CBOE SKEW index is useful in proxying investor sentiment. Investors prefer a higher skewness index, which represents greater investors' greed. These results are observed from stocks listed on both the NYSE and the NASDAQ. Moreover, investors might capture higher abnormal returns around recommendation upgrades and lose more around recommendation downgrades from stocks listed on the NASDAQ than those listed on the NYSE. In summary, this study provides significant implications for investors when making their investment decisions around news events in different stock exchanges.

The remainder of this paper proceeds as follows. Section 2 describes the data sample and reports the descriptive statistics. Section 3 presents the empirical results, and Section 4 concludes.

2. Data and descriptive statistics

We focus on analyst recommendation revisions for the NYSE-listed and NASDAQ-listed companies, from January 2002 to December 2019. We collect data from several data sources. Analyst recommendation data are from the Institutional Brokers' Estimate System (I/B/E/S) through the Wharton Research Data System (WRDS). I/B/E/S ranks recommendations from 1 (strong buy) to 5 (sell)[6]. For ease of interpretation, we

[4] The abnormal return is only negative and with a small magnitude on day −1 for ΔSKEW < 0. Taking the NYSE for example, the magnitude of abnormal return for ΔSKEW>0 is 0.60%, but it is only 0.13% for ΔSKEW < 0 (roughly one-fifth of that for ΔSKEW>0).

[5] Except for a smaller negative return on day −1 for ΔSKEW>0, the explanation for this is similar to that in footnote 3.

[6] Specifically, analyst recommendations in I/B/E/S are ranked as: 1 = Strong buy, 2 = Buy, 3 = Hold, 4 = Underperform, 5 = Sell.

follow Howe. et al. [29] and Loh and Stulz [30] and reverse the recommendation ratings so that the highest (lowest) rating represents the most (least) favorable recommendation. After reversing, we have 1 = Sell, 2 = Underperform, 3 = Hold, 4 = Buy and 5 = Strong buy.[7] We require any analyst recommendation to have a CUSIP number and a recommendation date.

We analyze revisions, rather than levels, in analyst recommendations. This is because Jegadeesh et al. [31] find that recommendation levels provide little incremental investment value relative to other investment signals, and Jegadeesh and Kim [14] show that recommendation changes are more informative than levels in predicting stock returns. We follow Loh and Stulz [30] and calculate the difference between current and prior ratings made by the same analyst. As recommendation levels range from 1 (sell) to 5 (strong buy), recommendation revisions range from −4 to +4. We define the recommendation revision with a positive (negative) value as an upgrade (downgrade). We omit zero recommendation revisions because zero changes suggest that the analysts possess no incremental new information. We also follow Barber et al. [32] and remove outdated observations whose prior recommendation exceeds 1 year. When multiple analysts issue recommendations for one stock within one trading day, we average all of the recommendation revisions. If the average value of recommendation revisions is positive (negative), we define it as an upgrade (downgrade) [33].

We collect stock prices from the Center for Research in Security Prices (CRSP) database. To be included in our sample, the stock must have a CUSIP number and have at least 251 trading days before, and 10 days after the corresponding recommendation revisions. The absolute daily historical stock return should not exceed 65% [16]. We identify stocks listed on the NYSE and the NASDAQ using the stock exchange code (EXCHCD). The NYSE-listed stock has an EXCHCD of 1 and the NASDAQ-listed stock has an EXCHCD of 3. The NYSE and the NASDAQ index prices are extracted from www.finance.yahoo.com. SKEW and VIX data are obtained from the CBOE website.[8]

Table 1 reports the yearly descriptive summary for the stocks listed on the NYSE (Panel A) and the NASDAQ (Panel B). The market capitalization (MarketCap) is computed as the share price multiplied by the total shares outstanding on the event day. The stock's market model beta is estimated over an estimate window [−251, −31] prior to the recommendation revision. For the NYSE, the MarketCap ranges from $1 to $461,021 million with a standard deviation of $31,130 million. The market model beta varies from −1.359 to 5.818 and the standard deviation is 0.486. The daily historical return ranges from −0.632% to 0.621%, with a standard deviation of 0.056%. We observe a very low mean and high standard deviation of stock returns in 2002 and around 2008 and 2009. It is very clear that the year 2008–2009 is related to the global financial crisis, but the year 2002 might be affected by the NASDAQ "bubble." [34] Accordingly, we observe a higher market model beta with a value of 1.21 in 2009 and 1.24 in 2016.

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[7] "Underperform" is a type of stock trading recommendation between "Sell" and "Hold". Clearly, analysts recommend that a stock's performance is below the average market performance. In different databases or analyst ranking systems, different terms may be used. For example, "Strong sell" and "Sell" would be used rather than "Sell" and "Underperform".

[8] https://www.cboe.com/us/indices/dashboard/skew/
http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data.

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Year	Number of Rec. revisions	MarketCap ($ millions)				Market model beta				Historical returns (%)			
		Mean	**Std.**	**Min**	**Max**	**Mean**	**Std.**	**Min**	**Max**	**Mean**	**Std.**	**Min**	**Max**
Panel A: NYSE													
2002	1841	11,412	26,932	1	297,139	1.010	0.555	−1.359	3.179	−0.009	0.072	−0.632	0.317
2003	2644	10,566	24,951	2	263,281	0.949	0.486	−0.407	3.001	0.000	0.049	−0.495	0.325
2004	2352	10,899	27,341	11	377,531	1.040	0.494	−0.272	4.064	−0.001	0.043	−0.341	0.231
2005	1990	12,389	30,657	2	407,438	1.173	0.451	−0.005	3.360	0.000	0.052	−0.568	0.360
2006	1892	12,434	27,143	14	399,501	1.101	0.465	0.034	2.998	0.000	0.047	−0.371	0.468
2007	2367	13,032	28,599	3	432,187	1.110	0.433	−0.063	2.604	−0.002	0.052	−0.630	0.547
2008	2971	12,390	26,933	4	461,021	1.127	0.406	0.045	3.108	−0.009	0.078	−0.627	0.512
2009	2752	9729	24,858	13	391,672	1.206	0.445	0.053	3.381	0.006	0.065	−0.475	0.568
2010	2158	12,043	26,594	14	316,848	1.169	0.490	0.008	3.052	0.001	0.045	−0.335	0.571
2011	2519	14,380	31,510	20	403,397	1.101	0.387	−0.248	2.506	0.005	0.047	−0.286	0.589
2012	2287	13,956	30,307	16	407,762	1.173	0.439	0.099	3.020	−0.001	0.048	−0.628	0.344
2013	1725	14,025	28,069	17	411,208	1.122	0.437	−0.028	3.251	0.001	0.047	−0.281	0.524
2014	1576	16,078	31,959	1	415,876	1.076	0.409	−0.102	3.177	0.000	0.045	−0.481	0.298
2015	1583	15,969	36,477	1	363,847	1.134	0.498	−0.179	3.778	−0.001	0.056	−0.535	0.439
2016	1768	16,176	36,698	15	340,695	1.242	0.585	−0.373	5.818	−0.002	0.063	−0.509	0.559
2017	1483	18,418	39,719	17	355,281	1.380	0.675	−0.241	4.905	−0.001	0.054	−0.352	0.621
2018	1264	22,934	49,778	20	401,343	1.107	0.497	−0.327	3.267	−0.001	0.053	−0.444	0.403
2019	1339	18,576	40,818	5	421,857	1.169	0.512	−0.609	3.102	−0.003	0.064	−0.572	0.448
Total	36,511	13,582	31,130	1	461,021	1.127	0.486	−1.359	5.818	−0.001	0.056	−0.632	0.621
Upgrades	18,124	13,859	30,439	1	461,021	1.132	0.489	−1.359	5.818	0.019	0.046	−0.630	0.589
Downgrades	18,387	13,310	31,795	1	422,622	1.121	0.482	−1.119	3.855	−0.020	0.058	−0.632	0.621

Year	Number of Rec. revisions	MarketCap ($ millions)				Market model beta				Historical returns (%)			
		Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Panel B: NASDAQ													
2002	1440	5029	21,513	3	293,626	0.859	0.577	−0.344	2.388	−0.014	0.095	−0.602	0.526
2003	2038	4217	19,361	4	288,100	0.877	0.527	−0.394	2.365	0.003	0.080	−0.646	0.594
2004	1896	5442	19,885	4	306,461	1.017	0.521	−0.290	3.017	−0.004	0.072	−0.408	0.537
2005	1886	4408	17,814	6	294,645	1.064	0.513	−0.183	2.673	−0.003	0.078	−0.635	0.520
2006	1928	4491	16,759	15	275,384	1.070	0.454	−0.356	2.517	0.002	0.078	−0.620	0.513
2007	1677	4442	16,696	7	304,443	1.079	0.430	−0.337	2.514	−0.001	0.082	−0.643	0.630
2008	2053	4903	18,223	3	297,172	1.004	0.367	−0.354	2.405	−0.011	0.101	−0.636	0.639
2009	2078	4233	15,793	5	210,114	1.098	0.378	−0.197	2.439	0.005	0.081	−0.612	0.484
2010	1705	6102	23,380	16	283,897	1.167	0.430	−0.040	2.684	0.001	0.065	−0.462	0.541
2011	1847	6386	19,960	11	369,044	1.141	0.376	−0.555	2.539	−0.001	0.074	−0.525	0.561
2012	1482	7758	39,746	12	654,966	1.204	0.378	0.005	2.624	−0.002	0.080	−0.498	0.545
2013	1086	10,172	39,767	23	464,875	1.053	0.350	0.048	2.212	0.001	0.087	−0.645	0.644
2014	949	11,372	46,923	19	604,775	1.118	0.448	−0.219	2.981	−0.002	0.086	−0.616	0.619
2015	1019	10,742	46,159	12	731,588	1.035	0.382	−0.237	2.598	0.002	0.090	−0.461	0.621
2016	1000	13,189	59,554	32	614,229	1.009	0.384	−0.339	2.591	−0.004	0.089	−0.616	0.590
2017	924	11,670	37,359	33	674,338	1.108	0.475	−0.236	2.941	−0.001	0.080	−0.541	0.615
2018	832	15,698	57,970	15	973,230	0.895	0.459	−0.575	2.484	0.000	0.087	−0.641	0.519
2019	959	23,537	90,062	4	1,105,306	0.940	0.419	−0.371	2.142	−0.004	0.090	−0.649	0.545
Total	26,799	7296	33,942	3	1,105,306	1.044	0.454	−0.575	3.017	−0.002	0.083	−0.649	0.644
Upgrades	13,055	7741	33,913	3	1,105,306	1.058	0.454	−0.575	2.981	0.033	0.065	−0.610	0.644
Downgrades	13,744	6873	33,965	3	973,230	1.032	0.455	−0.555	3.017	−0.034	0.085	−0.649	−0.630

Table 1.
Yearly sample descriptive statistics for stocks listed on the NYSE (Panel A) and the NASDAQ (Panel B).

For the NASDAQ, the MarketCap varies from \$3 to \$1,105,306 million with a standard deviation of \$33,942 million. The maximum MarketCap appears in 2019, which shows a large value increase in high-tech stocks in recent years. Interestingly, we observe a higher average market model beta with a value of 1.20 in 2012 rather than in the 2009 financial crisis period. The daily historical return ranges from −0.649% to 0.644%, with a standard deviation of 0.083%. It shows that the stock return is more volatile for the stocks listed on the NASDAQ. Similar to the NYSE, a very low mean and high standard deviation of stock returns are observed in 2002 and around 2008 and 2009. Pástor and Veronesi [34] show the NASDAQ "bubble" in the late 1990s, with the NASDAQ index price varying significantly from 5048 in March 2000 to 1114 in October 2002. This was accompanied by high return volatility, which is around 10%.

3. Empirical results

In this section, we present our empirical results for the NYSE and the NASDAQ. We define the analyst recommendation revision date as day 0. We begin the empirical analysis by investigating the daily abnormal return (AR) over the event window surrounding the analyst recommendation revision. We use the market model to calculate AR$_i$ [16]:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the daily return for stock i on date t, and $R_{m,t}$ is the market return. α_i and β_i are the corresponding regression coefficients, and $\varepsilon_{i,t}$ is the error term. We use the NYSE composite index return and the NASDAQ composite index return as the market returns, respectively. We estimate Eq. (1) using an estimation window that covers day −251 to day −30. Following Savor [35], we calculate the abnormal return AR$_{i,t}$ as:

$$AR_{i,t} = R_{i,t} - \hat{\beta}_i R_{m,t}, \tag{2}$$

where $\hat{\beta}_i$ is the estimated coefficient of market returns in Eq. (1).

Table 2 reports the average daily stock ARs for upgrades and downgrades over the [−10,+10] event window.[9] Panel A and Panel B are for the NYSE and NASDAQ, respectively. For visualization, we take the NYSE for example to plot the average ARs for downgrades (Panel A) and upgrades (Panel B) over this event window. **Figure 1** shows the plots.

For both the NYSE and the NASDAQ, we observe that abnormal stock returns increase (decrease) considerably on the day of recommendation upwards (downwards), that is, day 0 (or event day), with some abnormal behavior on day −1. This tendency reflects analysts' perspectives on stocks' performance - upgraded (downgraded) stocks might be underestimated (overestimated) after experiencing a period of negative (positive) ARs [16].

[9] We also calculate ARs for the event window [−30,+10] and obtain qualitatively similar results, which are available upon request.

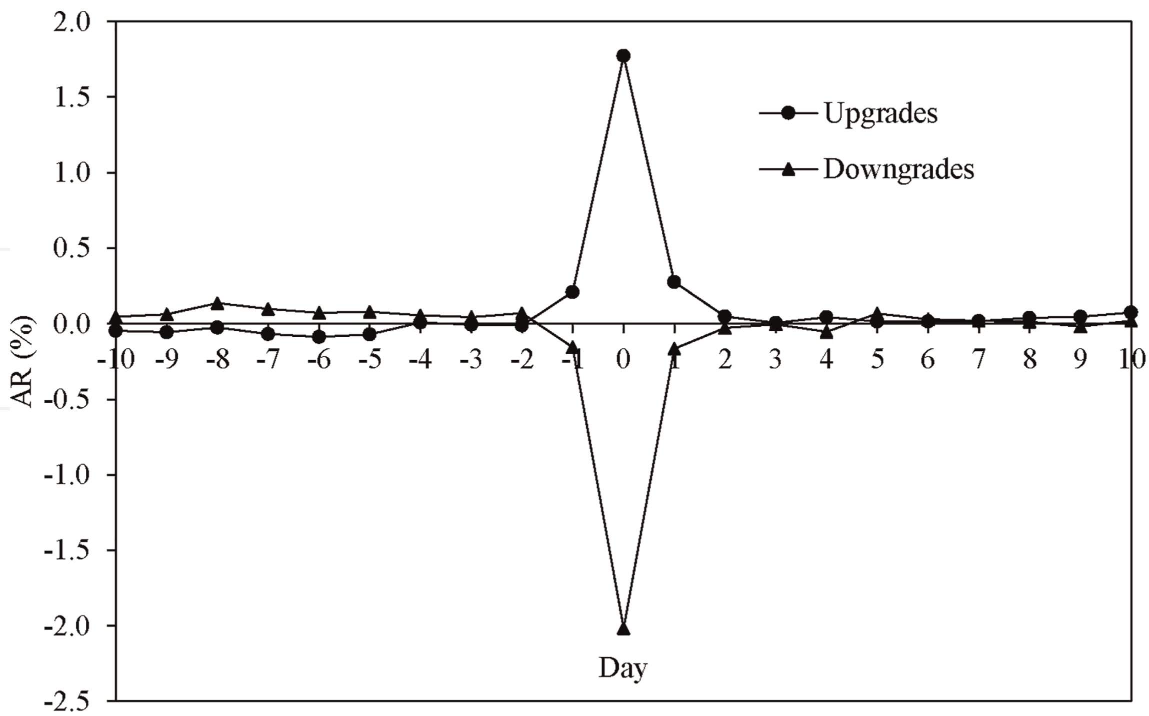

Figure 1.
Abnormal stock returns over the event window.This figure plots the abnormal stock returns over the [−10,+10] event window surrounding analyst recommendation revisions for the stocks listed on the NYSE.

Event window [−10,+10]	Upgrades		Downgrades	
	Average AR (%)	*t*-statistics	Average AR (%)	*t*-statistics
Panel A: NYSE				
−10	−0.05	−2.48	0.05	2.28
−9	−0.06	−2.93	0.06	3.28
−8	−0.02	−1.22	0.14	6.84
−7	−0.07	−3.50	0.10	5.21
−6	−0.09	−4.70	0.07	3.67
−5	−0.07	−3.65	0.08	3.86
−4	0.01	0.34	0.05	2.80
−3	−0.01	−0.33	0.04	1.98
−2	−0.01	−0.53	0.07	2.83
−1	0.21	7.36	−0.16	−4.25
0	1.77	55.80	−2.02	−49.19
1	0.28	13.78	−0.17	−7.76
2	0.05	2.67	−0.03	−1.27
3	0.01	0.30	0.00	−0.27
4	0.04	2.28	−0.05	−2.81
5	0.01	0.70	0.07	2.96
6	0.01	0.71	0.03	1.34
7	0.02	0.98	0.02	0.99
8	0.04	2.29	0.01	0.70
9	0.04	2.42	−0.02	−0.82
10	0.08	3.92	0.02	1.01
Panel B: NASDAQ				
−10	−0.07	−2.31	0.09	2.60
−9	−0.09	−3.69	0.04	1.70
−8	−0.07	−2.74	0.13	4.50
−7	−0.11	−4.43	0.15	5.54

Event window [−10,+10]	Upgrades		Downgrades	
	Average AR (%)	*t*-statistics	Average AR (%)	*t*-statistics
−6	−0.10	−3.51	0.14	4.82
−5	−0.16	−5.05	0.10	3.47
−4	−0.09	−3.31	0.11	3.77
−3	−0.05	−1.45	0.11	3.51
−2	-0.05	−1.68	0.18	4.63
−1	0.12	2.60	−0.12	−2.20
0	3.17	57.26	−3.47	−48.94
1	0.28	9.89	−0.22	−7.35
2	0.09	3.54	−0.10	−3.63
3	0.05	2.04	−0.08	−2.75
4	0.04	1.44	−0.05	−2.05
5	0.07	2.54	−0.01	−0.44
6	0.04	1.67	0.06	2.23
7	−0.02	−0.64	0.03	1.16
8	0.03	1.05	−0.01	−0.36
9	0.02	0.75	−0.04	−1.51
10	0.00	−0.13	0.00	0.16

Table 2.
The abnormal returns (ARs) around analyst recommendation revisions for the NYSE (Panel A) and the NASDAQ (Panel B).

Furthermore, we find that the corresponding increase or decrease of abnormal returns around recommendation revisions is larger for the NASDAQ than for the NYSE. Specifically, on day 0, the average abnormal return of upgrades (downgrades) is 3.17% (−3.47%) for the NASDAQ and 1.77% (−2.02%) for the NYSE. This suggests the potential difference of stocks and investor perspectives on these stocks between the NYSE and the NASDAQ. The firms listed on the NASDAQ are generally small and young, and accordingly, their share prices are highly volatile. For example, the mean of the MarketCap for stocks listed on the NASDAQ is $7296 million, much smaller than the mean of the MarketCap of $13,582 million for stocks listed on the NYSE. The average standard deviation of historical returns for stocks listed on the NASDAQ (0.083%) is higher than that for stocks listed on the NYSE (0.056%).

3.1 The effect of SKEW

Similar to Kliger and Kudryavtsev [16], we document a significant relationship between abnormal returns around recommendation revisions and contemporaneous SKEW changes (ΔSKEW). To compare with Kliger and Kudryavtsev [16], we also present the results concerning VIX in the next subsection.

3.1.1 The effect on day −1 and day 0

Table 3 reports the effect of SKEW on investors' reaction to analyst recommendation revisions on days −1 and 0.

Panels A and B present the results for the NYSE and the NASDAQ, respectively. ΔSKEW is the change of SKEW corresponding to day t for stock i's recommendation revisions. We show that the contemporaneous SKEW changes have a statistically significant effect on the abnormal returns around recommendation revisions. An increase (decrease) in SKEW is related to a larger (smaller) average AR for both

Type of recommendation revision	Average AR on day −1 (%)			Average AR on day 0 (%)		
	$\Delta SKEW > 0$	$\Delta SKEW < 0$	Diff (t-statistic)	$\Delta SKEW > 0$	$\Delta SKEW < 0$	Diff (t-statistic)
Panel A: NYSE						
Upgrades	0.60	−0.13	0.73*** (11.48)	2.25	1.52	0.73*** (10.67)
Downgrades	0.19	−0.43	0.62*** (8.02)	−1.70	−2.34	0.64*** (7.52)
Panel B: NASDAQ						
Upgrades	0.48	−0.19	0.67*** (7.15)	3.56	2.97	0.59*** (5.14)
Downgrades	0.29	−0.39	0.68*** (6.03)	−2.97	−3.90	0.93*** (6.43)

*Note: *, ** and *** denote significance levels at 10%, 5%, and 1%, respectively.*

Table 3.
The effect of contemporaneous daily changes in SKEW on the abnormal returns (ARs) around event days for the NYSE (Panel A) and the NASDAQ (Panel B).

upgrades and downgrades compared with the unconditional AR (see **Table 2**). Take the NYSE for example. For ΔSKEW > 0, the average AR on day −1 is 0.60% (0.19%) for upgrades (downgrades), however, for ΔSKEW < 0, it is −0.13% (−0.43%). The difference of the average AR between ΔSKEW > 0 and ΔSKEW < 0 is statistically significant, with a value of 0.73% (t-statistic = 11.48) for upgrades and 0.62% (t-statistic = 8.02) for downgrades.

On day 0, the corresponding average AR become more positive (negative) for upgrades (downgrades), manifested by the results shown in **Table 2**. Specifically, for ΔSKEW > 0, the average AR is 2.25% (−1.70%) for upgrades (downgrades); forΔSKEW < 0, it becomes 1.52% (−2.34%). The findings indicate that abnormal returns around analyst recommendation revisions are closely associated with contemporaneous SKEW changes. That is, positive events (upgrades) drive significantly higher ARs captured by the daily SKEW increase (i.e., a higher expectation of earnings, or greed), and negative events (downgrades) drive significantly lower ARs captured by the daily SKEW decrease (i.e., a lower expectation of earnings).

For the NASDAQ, the results are generally consistent with those for the NYSE. Interestingly, on day −1, we find that the magnitudes of average ARs for all cases (upgrades and downgrades, ΔSKEW > 0 and ΔSKEW < 0) are generally close to corresponding results of the NYSE. For example, for upgrades and ΔSKEW > 0, the average AR is 0.48% for the NASDAQ and 0.60% for the NYSE, with a difference of 0.12%. However, on day 0, the average ARs' corresponding magnitudes are larger for the NASDAQ than for the NYSE. Again, for upgrades and ΔSKEW > 0, the average AR is 2.25% for the NASDAQ and 3.56% for the NYSE, with a difference of 1.31%, almost ten times of that on day −1. On the one hand, this implies that SKEW is more informative on the event day than the day before. On the other hand, the findings indicate that recommendation revision may have a stronger effect on stocks listed on the NASDAQ than those listed on the NYSE. This is probably explained by the potential difference in the types of listing firms and the ways how investors perceive the firms. The NASDAQ is typically a high-tech market, the NASDAQ-listed firms are mainly technology, young and fast-growing firms. The stocks listed on the NASDAQ are considered to be more volatile (or say highly uncertain), and accordingly, investors demand a higher return [34]. Correspondingly, this high volatility (uncertainty) contributes to higher abnormal returns for recommendation upgrades but more negative abnormal returns for recommendation downgrades.

3.1.2 The effect on the cumulative days (−1,0)

Now we look at the effect of the changes in SKEW on the cumulative abnormal returns (i.e., CARs) over days −1 and 0. **Table 4** reports the results for both the NYSE (Panel A) and the NASDAQ (Panel B). Cumulative ΔSKEW represents the contemporaneous cumulative changes in SKEW over days −1 and 0. We present further evidence that SKEW has a statistical and economic effect on stock returns around analyst recommendations. That is, we find similar return patterns for Cumulative ΔSKEW to those on separated single days (i.e., day −1 and day 0). Taking the NYSE for example, for upgrades, the significantly *positive* difference (i.e., Diff = 0.83% with t-statistic = 8.93) indicates that the CAR (with a value of 2.53%) is stronger when the cumulative change in SKEW is *positive* (i.e., Cumulative ΔSKEW > 0) than that (with a value of 1.70%) when the cumulative change in SKEW is *negative* (i.e., Cumulative ΔSKEW < 0). For downgrades, the significantly *positive* difference (i.e., Diff = 0.57% with t-statistic = 4.89) also indicates that the CAR (with a value of −1.87%) is stronger when the cumulative change in SKEW is *positive* (i.e., Cumulative ΔSKEW > 0) than that (with a value of −2.45%) when the cumulative change in SKEW is *negative* (i.e., Cumulative ΔSKEW < 0).

Next, we find that the corresponding magnitudes of the CARs are larger for the NASDAQ than the NYSE. In summary, these results provide further evidence supporting the hypothesis that abnormal returns around analyst recommendation revisions are closely correlated with contemporaneous changes in SKEW.

3.1.3 Additional tests

To further validate the event results obtained in Section 3.1, we apply a simple regression model (i.e., univariate model) to test whether SKEW could act as one measure of investors' greed or fear. We write the regression model as [7]:

$$AR_{i,t} = \alpha + \beta \Delta \mathrm{SKEW}_t + \varepsilon_{i,t}, \tag{3}$$

In the regression analysis, we take day 0 for example and present the results in **Table 5**. From Panel A, we observe that the regression coefficient on the changes in SKEW (i.e., ΔSKEW) is positive and significant, with a value of 0.11 (t-statistic = 9.81) for upgrades and 0.09 (t-statistic = 5.85) for downgrades. These results suggest that an

Type of recommendation revision	**CAR over days −1 and 0 (%)**		
	Cumulative $\Delta SKEW > 0$	**Cumulative $\Delta SKEW < 0$**	**Diff (t-statistic)**
Panel A: NYSE			
Upgrades	2.53	1.70	0.83*** (8.93)
Downgrades	−1.87	−2.45	0.57*** (4.89)
Panel B: NASDAQ			
Upgrades	3.76	3.06	0.70*** (4.79)
Downgrades	−3.04	−3.94	0.90*** (4.89)

*Note: *, ** and *** denote significance levels at 10%, 5%, and 1%, respectively.*

Table 4.
The effect of changes in SKEW on the cumulative abnormal returns (CARs) for the NYSE (Panel A) and the NASDAQ (Panel B).

	Upgrades	Downgrades
Panel A:		
ΔSKEW	0.11*** (9.81)	0.09*** (5.85)
Intercept	1.88*** (55.0)	−2.03*** (−47.50)
Panel B:		
$\Delta SKEW^{+}$	0.10*** (5.31)	0.05* (1.88)
$\Delta SKEW^{-}$	0.13*** (6.17)	0.13*** (5.01)
Intercept	1.91*** (40.0)	−1.95*** (−33.08)

Note: The numbers in parentheses are t*-statistics. *, ** and *** denote significance levels at 10%, 5%, and 1%, respectively.*

Table 5.
Regression results for the abnormal returns (ARs) and the changes in SKEW (ΔSKEW) on recommendation revision days.

increase in SKEW is associated with an increase in abnormal returns regardless of recommendation upgrades or downgrades. Consistent with the event results presented in Sections 3.1.1 and 3.1.2, we argue that SKEW should be a proper measure of investors' greed.

We also examine the effect of positive and negative changes in SKEW on stock abnormal returns by separatingΔSKEW into the positive part (i.e., $\Delta SKEW^{+}$) and the negative part (i.e., $\Delta SKEW^{-}$). We estimate the following regression:

$$AR_{i,t} = \alpha + \beta_1 \Delta SKEW_t^{+} + \beta_2 \Delta SKEW_t^{-} + \varepsilon_t, \tag{4}$$

where $\Delta SKEW^{+}$ and $\Delta SKEW^{+}$ are defined as:

$\Delta SKEW_t^{+} = \Delta SKEW_t$, if $\Delta SKEW_t > 0$; otherwise $\Delta SKEW_t^{+} = 0$, and

$\Delta SKEW_t^{-} = \Delta SKEW_t$, if $\Delta SKEW_t < 0$; otherwise $\Delta SKEW_t^{-} = 0$.

Panel B in **Table 5** reports the results. Again, regardless of upgrades or downgrades, we observe positive and significant estimated coefficients on both $\Delta SKEW^{+}$ and $\Delta SKEW^{-}$. We also use Eqs. (3) and (4) to test the effect of changes in SKEW on the day prior to recommendation revisions (i.e., day −1), and obtain qualitatively similar results.[10] In summary, these results provide further evidence that SKEW could be considered as an investors' greed indicator.

3.2 The effect of VIX[11]

3.2.1 The effect on day −1 and day 0

To make a comparison with VIX, we test the relationship between changes in VIX (ΔVIX) and abnormal returns around recommendation revisions. Kliger and Kudryavtsev [16] only examine stocks listed on the NYSE. We extend our tests to stocks listed on the NASDAQ as well. **Table 6** reports the results on days −1 and 0.

Panels A and B present the results for the NYSE and the NASDAQ, respectively. ΔVIX is the change of VIX price corresponding to day *t* for stock *i*'s recommendation revisions. Consistent with the findings of Kliger and Kudryavtsev [16], the

[10] The results are not reported but are available upon request.

[11] The effect of VIX is examined in [16], which only includes firms listed on the NYSE. The purpose of Section 3.2 has twofold. First, we compare the different effects of SKEW and VIX. Second, we extend the test in [16] and compare the effect of VIX on firms listed on the NYSE and those listed on the NASDAQ.

Type of recommendation revision	Average AR on day −1 (%)			Average AR on day 0 (%)		
	$\Delta VIX > 0$	$\Delta VIX < 0$	Diff (t-statistic)	$\Delta VIX > 0$	$\Delta VIX < 0$	Diff (t-statistic)
Panel A: NYSE						
Upgrades	−0.76	1.17	−1.93*** (−31.12)	0.84	2.67	−1.83*** (−26.80)
Downgrades	−0.96	0.70	−1.66*** (−21.63)	−2.97	−1.25	−1.72*** (−20.34)
Panel B: NASDAQ						
Upgrades	−0.80	1.05	−1.85*** (−20.05)	2.18	4.02	−1.84*** (−15.93)
Downgrades	−0.81	0.70	−1.51*** (−13.34)	−4.43	−2.64	−1.79*** (−12.31)

*Note: *, ** and *** denote significance levels at 10%, 5%, and 1%, respectively.*

Table 6.
The effect of contemporaneous daily changes in VIX on the abnormal returns (ARs) around event days for the NYSE (Panel A) and the NASDAQ (Panel B).

contemporaneous VIX changes have a statistically significant effect on the abnormal returns around recommendation revisions. An increase (decrease) in VIX is associated with a smaller (larger) average AR for both upgrades and downgrades compared with the unconditional AR (see **Table 2**).

However, the results for changes in VIX are in contrast to those for changes in SKEW. Take the NYSE, day 0 and upgrades for example. For ΔVIX > 0, the average AR is 0.84%, but for ΔVIX < 0, it becomes larger with a value of 2.67%. These results indicate that a higher abnormal return is associated with a *decrease* in VIX (i.e., decrease in investors' fear). However, for ΔSKEW > 0, the average AR is 2.25%, but for ΔSKEW < 0, it becomes smaller with a value of 1.52%, which suggests that a higher abnormal return is related to an *increase* in SKEW (i.e., increase in investors' greed).

For the NASDAQ, the results are generally consistent with those for the NYSE. Again, on day −1, the corresponding magnitudes of the average AR for all cases are very close to those for the NYSE. However, on day 0, the corresponding magnitudes of the average AR are larger for the NASDAQ than for the NYSE. In the comparison between the NYSE and the NASDAQ, the results related to VIX are in line with those associated with SKEW. Overall, these results patterns could commonly be explained by the potential difference in the types of listing firms and the ways how investors perceive the firms listed on the different stock exchanges.

3.2.2 The effect on the cumulative days (−1,0)

We also examine the effect of the changes in VIX on the CARs over days −1 and 0. **Table 7** presents the results. Panel A is for the NYSE and Panel B is for the NASDAQ. Cumulative ΔVIX represents the contemporaneous cumulative changes in VIX over days −1 and 0. Our results for the NYSE are consistent with those of Kliger and Kudryavtsev [16].[12] For upgrades, the statistically significant *negative* difference indicates that the CARs are stronger when the cumulative change in VIX is *negative* (i.e., Cumulative ΔVIX < 0) than that when the cumulative change in VIX is *positive* (i.e., Cumulative ΔVIX > 0). However, for downgrades, the statistically significant *negative* difference suggests that the CARs are stronger when the cumulative change in VIX is *positive* (i.e., Cumulative ΔVIX > 0) than that when the cumulative change in VIX is *negative* (i.e., Cumulative ΔVIX < 0).

[12] Kliger and Kudryavtsev [16] do not test stocks listed on the NASDAQ.

Type of recommendation revision	CAR over days −1 and 0 (%)		
	Cumulative $\Delta VIX > 0$	Cumulative $\Delta VIX < 0$	Diff (t-statistic)
Panel A: NYSE			
Upgrades	0.73	3.28	−2.55*** (−27.70)
Downgrades	−3.32	−1.09	−2.23*** (−19.14)
Panel B: NASDAQ			
Upgrades	1.96	4.64	−2.68*** (−18.34)
Downgrades	−4.73	−2.36	−2.37*** (−12.94)

*Note: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.*

Table 7.
The effect of changes in VIX on the cumulative abnormal returns (CARs) for the NYSE (Panel A) and the NASDAQ (Panel B).

In comparison with the NYSE, we show that the corresponding magnitudes of the CARs are larger for the NASDAQ. It is in line with the argument that the telecoms industry is more sensitive to changes in investor sentiment. In short, these findings provide further evidence supporting the hypothesis stating that abnormal returns around recommendation revisions are correlated with contemporaneous changes in VIX [16].

Overall, our results of SKEW and VIX show that SKEW and VIX can act as different measures for investor sentiment in the financial markets. That is, SKEW measures investors' greed while VIX is an investors' fear gauge.

4. Conclusions

We investigate the effect of the CBOE SKEW index on the investors' reaction to analyst recommendations. We hypothesize that the abnormal returns around analyst recommendation revisions are closely correlated with contemporaneous SKEW changes. Our results for both the NYSE and the NASDAQ confirm this hypothesis. We show that when SKEW increases (i.e., increase in investors' greed) before or on the recommendation announcement days, investors could achieve higher average abnormal returns than the case with decreasing SKEW. That is, investors might gain more if they invest in stocks with upgrade recommendations during the period with an increase in SKEW. This is because investors are more optimistic and excited about the performance of the stock market. Furthermore, we observe that investors could gain higher average abnormal returns on days of upgrades and lose more on days of downgrades when investing in stocks listed on the NASDAQ than those listed on the NYSE.

We also examine the effect of VIX on the investors' reaction to analyst recommendations. The results are consistent with the findings of Kliger and Kudryavtsev [16]. Our results further demonstrate that SKEW and VIX show different effects on the financial markets. VIX is normally considered as an investors' fear gauge, but we show that SKEW could be considered as a measure for investors' greed, supported by a significantly positive relationship between the changes in SKEW and abnormal stock returns, regardless of recommendation upgrades or downgrades.

Our study complements prior literature on investor sentiment and financial markets. Han [17] documents a relation between index risk-neutral skewness [36] and investor sentiment, suggesting that the impact of investor sentiment is economically significant. With the development of various skewness measures, such as realize skewness [37], average skewness [38], systematic and idiosyncratic skewness [39], and other types of skewness [40], one of potential research directions could be examining these skewness measures in proxying investor sentiment and investors' behavior. Moreover, linking different skewness measures to a variety of corporate events (e.g., earnings announcements, dividend announcements, mergers, and acquisitions) and different stock exchanges is also worthwhile since difference skewness measures may incorporate different information, which provides useful insights for investors in making investment decisions.

JEL classification

D81; D84; G11, G14, G40.

Author details

Qingxia (Jenny) Wang[1,2]

1 Centre for Applied Climate Sciences, University of Southern Queensland, Toowoomba, Queensland, Australia

2 The University of Queensland, Brisbane, Queensland, Australia

*Address all correspondence to: jenny.wang2@usq.edu.au

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