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Extreme Sentiment and Jumps in Analyst Forecast Dispersion

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ABSTRACT

We study the effects of extreme sentiment on analyst forecast dispersion using the COVID-19 pandemic as a natural experiment, building on China's unique experimental environment. Employing manually collected data, we find that unlike common sentiment measured by air quality and investor sentiment, extreme sentiment stemming from the COVID-19 pandemic leads to jumps in analyst forecast dispersion. After controlling for common sentiment, the effect remains. Our study suggests that jumps in analyst forecast dispersion can be explained by extreme sentiment.

1. Introduction

Behavioral finance literature indicates that sentiment significantly affects various aspects of capital markets, including analyst forecasts and stock returns (Hribar and McInnis, 2012; Dong et al., 2021). This literature has pioneered a range of sentiment measures. Baker and Wurgler (2006) employed principal component analysis to construct a sentiment index by amalgamating multiple market sentiment indicators. Goetzmann et al. (2015) and Dong et al. (2021), respectively, utilized cloud cover and air pollution as proxies for exogenous emotional shocks. Other studies have employed data mining and text analysis to extract investor sentiment from sources like media reports and social platforms (Da et al., 2015; Edmans et al., 2022). However, these studies primarily capture common sentiments, with few delving into the impact of extreme sentiment on analyst behavior.

The COVID-19 pandemic provides a natural experiment for examining how extreme sentiment triggered by extreme negative events influences analyst forecasts. The strength, scale, and nature of the COVID-19 crisis have been unprecedented, profoundly affecting people's work and daily lives and seriously disrupting almost every aspect of the economy (Goldstein et al., 2021; Spiegel and Tookes, 2021). It has been accompanied by high fatality and infection rates, widespread job losses, economic recession, and significant uncertainty, inducing extreme anxiety and panic among people (Fetzer et al., 2021). Thus, through COVID-19, we can investigate how extreme sentiment, distinct from common sentiments, impacts analyst forecasts.

Resent research further indicates that extreme negative events, such as terrorist attacks and mass shootings, can exert a strong impact on individual sentiment and lead to inaccurate assessment of risks in unrelated domains (Slovic et al.,2007; Cuculiza et al., 2021). Hence, we expect that in regions heavily affected by COVID-19 pandemic, analysts are likely to experience amplified anxiety and panic, thereby influencing their expectations concerning company earnings. As the pandemic spread, disagreement among analysts located in affected and unaffected area about earning expectations surged. We thus conjecture that when analysts' residing cities

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transition into affected areas, the subsequent extreme sentiment may influence analysts' decisions, resulting in substantial divergent forecasts between analysts in affected and unaffected areas. (Hypothesis).

China has implemented distinctive epidemic prevention and control measures. The classification of middle- and high-risk areas provides a natural testing ground to examine the impact of extreme sentiment on analyst forecasts at the city level. This economic setting allows us to identify the impact of analyst mood on forecasting behavior more precisely. In particular, we are able to compare forecasts issued by analysts located in risk area with the forecasts of analysts located in risk-free area for the same firm and at the same time. When analysts' residing cities transition into risk areas, the subsequent extreme sentiment can influence analysts' decisions, resulting in substantial divergent forecasts between analysts in risk and risk-free areas. As depicted in Fig. 1, when a city shifts from a risk-free area to a risk area, there is a significant jump in analyst forecast dispersion. In our empirical tests, we find that unlike common sentiment, the extreme sentiment caused by a city transitioning into a risk area leads to significant jumps in analyst forecast dispersion, which employs manually collected daily city risk conditions and analyst contact information. Even after controlling for common sentiment, the result remains significant.

Our study contributes to the literature in two respects. First, we extend the literature that examines whether analyst forecasts are affected by sentiment. The existing literature documents how common sentiment measured by investor sentiment and weather condition affects analyst forecasts (Hribar and McInnis, 2012; Dong et al., 2021). By employing manually collected data during Covid-19 pandemic, we show that unlike common sentiment, extreme sentiment stemming from the pandemic leads to significant jumps in analyst divergence. Second, we complement the literature that analyzes the economic implications of Covid-19 pandemic from the perspective of analysts (Goldstein et al., 2021; Spiegel and Tookes, 2021; Li et al., 2021; O'Hara and Zhou, 2021; Lööf et al., 2022; Zhang et al., 2022). We show that Covid-19 pandemic can affect financial markets through their impact on analyst sentiment and, subsequently, forecasts.

2. Data and research design

2.1. Data and Sample

We obtained analysts' earnings forecasts, analysts' basic information, and listed companies' financial data from the CSMAR database. Daily risk status data for each city were manually collected from the official website of the State Council of China. To identify the city of residence for analysts, we manually collected contact information from research reports and determined analysts' geographical location by matching the area codes of landline phone numbers, thus aligning with the risk status of the city where analysts are located.

Our sample encompasses all daily observations from 2020 to 2022. We excluded samples where members of analyst teams were not located in the same city, as well as forecasts spanning over one year and samples with missing variables. Finally, we winsorized continuous variables at 1%.

2.2. Model and Variables

We use Eq. (1) to test the impact of the pandemic on analyst forecast dispersion.

$$Jump_{i,j,t} = \beta Treat_{i,t} + \gamma' X_{i,j,t} + Analyst_i + Firm_j + Time_t + \varepsilon_{i,j,t} \quad (1)$$

In order to cleanly identify changes after becoming a risky area, we designate the day on which a city transitions into a middle- or high-risk state, with at least a 30-day interval, as the event day. We select a window period comprising the 7 days preceding the event

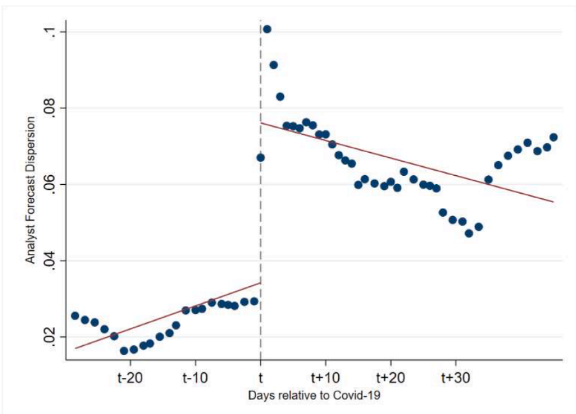

Fig. 1. Analyst forecast dispersion response to the Covid-19 pandemic

day and the 15 days following it. If the city where the analyst is located shifts from a risk-free area to a middle- or high-risk area, the independent variable *Treat* is assigned a value of 1, and 0 if the city remains a risk-free area throughout the event period.

To measure the alteration in analyst forecast dispersion subsequent to a city's designation as a middle- or high-risk area, we adopt the methodology proposed by Weller (2018) for constructing the "jump ratio". We construct the dependent variable *Jump* as the average analyst forecast dispersion during the days surrounding the event divided by the average analyst forecast dispersion before the event day. The analyst forecast dispersion is the dispersion of analyst forecasts compared to the consensus forecast. The consensus forecast is equal to the average value of the latest forecasts issued by all analysts in risk-free area towards the same target firm during the event period.

X is a vector of control variables. Following Dong et al. (2021) and Hribar and McInnis (2012), we control for firm-level and analyst-level characteristics as shown in Appendix Table A.1. We also control for *Analyst, Firm*, and *Time* fixed-effects.

3. Results and discussions

3.1. Benchmark regression

Table 1 presents the results from estimating Eq. (1). Columns (1)-(4) include different fixed effects. The coefficients of *Treat* are significantly positive at the 1% confidence level. This shows that when analysts' cities transition from risk-free areas to middle- or high-risk areas, the extreme sentiment generated in analysts can impact their decisions, leading to substantial jumps in analyst forecast

Table 1

Baseline results. This table presents the regression results of the Covid-19 pandemic on the jumps in analyst forecast dispersion. *Treat* is assigned a value of 1 if the city where the analyst is located shifts from a risk-free area to a middle- or high-risk area, and 0 if the city remains a risk-free area throughout the event period. *Jump* is the average analyst forecast dispersion during the days surrounding the event divided by the average analyst forecast dispersion before the event day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, with t values in parentheses.

	Jump			
	(1)	(2)	(3)	(4)
Treat	0.424***	0.296***	0.944***	0.587***
	(5.94)	(4.19)	(11.28)	(7.11)
AnaAttention	1.523***	1.525***	1.563***	1.593***
	(40.93)	(40.20)	(13.06)	(13.25)
Inst	0.001	0.001	0.008	0.007
	(0.46)	(0.48)	(1.10)	(1.01)
BM	0.468***	0.485***	-1.215**	-1.159**
	(3.82)	(3.95)	(-2.53)	(-2.41)
Shrcr_5	0.008***	0.008***	0.015	0.011
	(3.60)	(3.53)	(1.08)	(0.77)
ROA	-0.265	-0.235	-0.802	-0.678
	(-0.39)	(-0.34)	(-0.60)	(-0.51)
Size	0.059*	0.060*	-0.230	-0.200
	(1.71)	(1.73)	(-1.34)	(-1.16)
EPSv	-0.000**	-0.000**	0.000	0.000
	(-2.49)	(-2.49)	(0.37)	(0.07)
Past 12m returns	0.095**	0.092**	0.024	0.009
	(2.12)	(2.05)	(0.36)	(0.13)
Star	-0.447**	-0.426**	-0.563**	-0.686***
	(-2.42)	(-2.30)	(-2.44)	(-2.98)
Degree	0.206***	0.194***	0.104	0.125
	(3.09)	(2.80)	(1.19)	(1.37)
Forecast_Num	0.064	0.128	-0.052	-0.014
	(0.75)	(1.45)	(-0.47)	(-0.12)
FollowCo_Num	-0.047	-0.149	0.174	0.101
	(-0.46)	(-1.40)	(1.34)	(0.75)
Ana_Experience	0.046	0.052	-0.026	0.019
	(1.25)	(1.37)	(-0.56)	(0.41)
Broker_size	-0.035	-0.021	0.013	-0.023
	(-1.02)	(-0.56)	(0.29)	(-0.46)
Forecast Horizon	-0.008***	-0.008***	-0.007***	-0.007***
	(-8.65)	(-8.71)	(-6.01)	(-5.82)
Accuracy_last	0.047***	0.046***	0.051**	0.038*
	(3.14)	(3.13)	(2.35)	(1.78)
City FE	NO	YES	NO	YES
Stock FE	NO	NO	YES	YES
Time FE	YES	YES	YES	YES
Observations	35,722	35,722	35,502	35,502
R-squared	0.216	0.216	0.315	0.318

dispersion.

3.2. Extreme Sentiment and Common Sentiment

In this section, we will explore the distinction between extreme sentiment and common sentiment, aiming to clarify whether our results persist after controlling for regular sentiment. We utilize the two most common indicators in the literature, air quality and individual stock investor sentiment, to measure ordinary sentiment.

Motivated by Dong et al. (2021), we used a city's relative air quality index (AQI) to measure the change in weather conditions before and after the release of analyst forecasts. Table 2 reports the result. The coefficients of *AQI_1* and *AQI_2* are insignificant, which implies that while common sentiment measured by air quality can indeed influence analyst forecast dispersion, it does not lead to a jump in this dispersion. The coefficients of *Treat* remain positive at the 1% significance level in columns (2) and (4) of Table 2, indicating that even after controlling for common sentiment, the extreme sentiment stemming from a city transitioning into a middle- or high-risk area can still result in jumps in analyst forecast analysis.

Subsequently, we construct city-level investor sentiment based on individual stock investor sentiment. Table 3 reports the result. The coefficients of *InvSent_1* and *InvSent_2* are insignificant. The *Treat* coefficients are still significantly positive. The results suggest that investor sentiment does not lead to jumps in analyst forecast analysis. Even after controlling for investor sentiment, the extreme sentiment caused by a city transitioning into a risk area can still result in significant jumps in analyst forecast dispersion. In general, unlike common sentiment, it is extreme sentiment that triggers jumps in analyst forecast analysis.

3.3. Robustness test

In this section, we examine whether our results are robust using alternative regression specifications.

We perform sensitivity analysis on the event window. Columns (1) and (2) of Table 4 report the regression results for the windows [-7, 20] and [-10, 20], respectively. The coefficients of *Treat* remain significantly positive.

Moreover, we conduct a placebo test. In particular, for each transition of risk status, we randomize the location. The results in columns (3) of Table 4 show that the *Treat* coefficient estimate is not significant when we randomize attack locations.

A possible alternative explanation for our findings could be that Covid-19 pandemic is related to the macroeconomic environment of the state in which they occur, which could subsequently affect analysts' risk attitudes and expectations. To control for this possibility, we reestimate our baseline specification and include GDP and unemployment rate of each province as control variables. The estimates reported in columns (4) of Table 4 indicate that even when we account for a city's economic environment, the effect remains.

4. Conclusion

Taking advantage of China's distinctive experimental context, we manually gathered daily city risk assessments and analyst contact information to analyze the impact of the extreme negative events on analysts at the city level. We find that when analysts' cities transition from risk-free areas to middle- or high-risk areas, the extreme sentiment generated in analysts can impact their decisions, leading to substantial jumps in analyst forecast dispersion. Moreover, common sentiment measured by air quality and investor sentiment cannot lead to a jump in analyst forecast dispersion. After controlling for common sentiment, the extreme sentiment stemming from a city transitioning into risk areas can still result in jumps in analyst forecast analysis.

Table 2

Air quality index. We still use Eq.(1) with same control variables and fixed effects, only replacing the independent variable *Treat* with air quality index in columns (1) and (3). Moreover, we re-estimate our baseline specification and include air quality index as control variables in columns (2) and (4). *AQI_1* and *AQI_2* are the city's relative air quality index, measuring the change in weather conditions before and after the release of analyst forecasts. *Jump* is the average analyst forecast dispersion during the days surrounding the event divided by the average analyst forecast dispersion before the event day. *Treat* is assigned a value of 1 if the city where the analyst is located shifts from a risk-free area to a middle- or high-risk area, and 0 if the city remains a risk-free area throughout the event period. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, with t values in parentheses.

	Jump			
	(1)	(2)	(3)	(4)
Treat		0.601***		0.591***
		(7.16)		(7.12)
AQI_1	0.001	-0.002		
	(0.16)	(-0.80)		
AQI_2			0.002	-0.000
			(0.94)	(-0.20)
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	35,502	35,502	35,502	35,502
R-squared	0.317	0.317	0.318	0.318

Table 3
Investor sentiment. We still use Eq. (1) with same control variables and fixed effects, only replacing the independent variable *Treat* with investor sentiment in columns (1) and (3). Moreover, we re-estimate our baseline specification and include investor sentiment as control variables in columns (2) and (4). *InvSent_1* and *InvSent_2* are the city-level investor sentiment based on individual stock investor sentiment. *Jump* is the average analyst forecast dispersion during the days surrounding the event divided by the average analyst forecast dispersion before the event day. *Treat* is assigned a value of 1 if the city where the analyst is located shifts from a risk-free area to a middle- or high-risk area, and 0 if the city remains a risk-free area throughout the event period. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, with t values in parentheses.

	Jump			
	(1)	(2)	(3)	(4)
Treat		0.441***		0.441***
		(4.72)		(4.72)
InvSent_1	-0.210	-0.154		
	(-1.25)	(-0.92)		
InvSent_2			-0.256	-0.199
			(-1.30)	(-1.01)
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	23,775	23,775	23,775	23,775
R-squared	0.293	0.293	0.293	0.293

Table 4
Robustness Test. This table presents the results using alternative regression specifications. Columns (1) and (2) report the regression results for the windows [-7, 20] and [-10, 20], respectively. Columns (3) presents the result of placebo test. In columns (4), we reestimate our baseline specification and include GDP and unemployment rate of each province as control variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, with t values in parentheses.

	Jump			
	(1)	(2)	(3)	(4)
Treat	0.804***	0.508***	0.302	0.382***
	(7.07)	(5.44)	(0.34)	(4.11)
GDP				0.005**
				(2.44)
Unemployment				0.368
				(0.62)
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	34,509	36,031	3592	35,502
R-squared	0.316	0.326	0.212	0.319

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CRediT authorship contribution statement

Pan Li: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Kecai Chen:** Writing – review & editing, Validation, Investigation, Data curation. **Xiaoneng Zhu:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2024.105113.

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