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Highlights

- This paper investigates the effect of the COVID-19 pandemic on analysts' forecast dispersion. We find that analysts' exposure to the COVID-19 lockdown reduces the dispersion of their forecasts.
- Along with the forecast dispersion, the number of earnings forecasts issued by treated analysts decreases, supporting the channel of attention distraction.
- Moreover, there is no significant difference between optimistic and pessimistic forecasts, against the explanation of risk attitude change.
- We find our conclusion is robust to a staggered DID model and numerous robustness tests.

Abstract: This paper investigates the effect of the COVID-19 pandemic on analysts' forecast dispersion. We find that analysts' exposure to the COVID-19 lockdown reduces the dispersion of their forecasts. Along with the forecast dispersion, the number of earnings forecasts issued by treated analysts decreases, supporting the channel of attention distraction. Moreover, there is no significant difference between optimistic and pessimistic forecasts, against the explanation of risk attitude change. We find our conclusion is robust to a staggered DID model and numerous robustness tests. Our finding contributes to the dispute regarding the pandemic's effect on analyst forecast behavior.

Keywords: COVID-19 pandemic; Analysts' forecast dispersion; Limited attention

1. Introduction

While the forecasts of sell-side analysts are useful information for stock pricing, the literature alerts that analyst forecasts can be biased and investors should be cautious when using this information (Gao et al., 2021). Given the difficulties in directly measuring analysts' bias, existing studies usually examine whether exposure to extremely negative events that are unrelated to financial markets, i.e., exogenous, shocks analysts' sentiment and affects their forecasts. For instance, the COVID-19 pandemic provided an ideal setting and a few studies took this chance. However, extant studies have yet to reach a consensus regarding the effect of COVID-19 on analysts' bias. Vacca (2020) finds that analysts who are more exposed to the virus tend to herd more closely with the consensus forecast. Gao et al. (2021) document a positive impact of COVID-19 on analysts' forecast dispersion for firms in pandemic-exposed zones, in other words, away from the consensus forecast. A common point of these two papers is that they measure exposure to the virus with the number of COVID-19 victims. However, connecting the number of victims and analysts' mobility with a simple linear relationship is lack of support from the reality of different mobility restrictions in different states (provinces) in the U.S. (China), which could be a source of the inconsistency in their findings.

In this paper, we use the classification of middle- and high-risk pandemic areas in China to study how the COVID-19 crisis affects analysts' forecasting behaviors. The State Council of China started the level-I response and centralized the decision-making power on public policies to combat the pandemic since the outbreak of the pandemic in Wuhan in early 2020. But when the pandemic was gradually brought under control in many provinces by late February 2020, the power of making decisions against the pandemic was transferred to the provincial governments. The provincial governments can define whether a region with confirmed victims should be classified as a middle-/high- risk pandemic or not, based on the number, source, and distribution of victims. Since then, the lockdown restrictions were also gradually lifted across different regions, giving us a chance to conduct our study. The advantages of choosing this setting include: First, the lockdown policy in China is strictly enforced since the outbreak of the pandemic in Wuhan in early 2020 and is still valid today. Second, the mobility restriction of middle- and high-risk areas keeps consistent across different regions in China. Moreover, the local governments define the middle- and high-risk areas based on the number, source, and distribution of COVID-19 victims, instead of simply relying on counting the victim's number.

The prediction of the COVID-19 crisis on analysts' forecasting dispersion is two-sided. On the one hand, exposure to the pandemic can increase the dispersion of analysts' forecasts to consensus. First, the psychology literature documents that people exposed to extreme negative events are likely to become pessimistic in their assessment of risks in unrelated domains. For example, Cuculiza et al. (2020) show that sell-side analysts located near terrorist attacks will issue more pessimistic earnings forecasts following these events, compared with forecasts of non-local analysts for the same firm. The pandemic may likewise have the same effect on analysts' sentiment, but this is only significant in pessimistic forecasts rather than optimistic ones. Second, while analysts issue forecasts based on their unique information of the target firms and most unique information comes from site visits, the pandemic caused information lockdown due to the strict mobility restrictions and reduced long-distance travel (Gao et al., 2021). It results in more divergent analysts' forecasts, especially for opaque target firms.

On the other hand, exposure to COVID-19 can decrease analysts' forecast dispersion. First, the shock of a pandemic can affect analysts' attitudes towards risk. Given that departing from the consensus forecast is inherently risky for analysts, they are likely to reduce dispersion when the pandemic makes them risk-averse (Vacca, 2020). The effect would be more pronounced for the first wave of the pandemic because the attitude towards risk changes much when first facing the shock. Second, the decreasing dispersion may come from analysts' lack of effort during the pandemic. Analysts might face attention limits resulting from the distraction of experiencing the virus by their family members, relatives, colleagues, and themselves. The distraction of attention will decrease their ability to play the role of revealing information during a short period (Dong and Heo, 2014).

In our empirical tests, we find evidence supporting the negative effect of the COVID-19 pandemic on analysts' forecast dispersion. Moreover, we verify the channel of attention distracted by the pandemic, instead of the changes in risk attitude. We conduct a staggered DID model and numerous robustness tests and find our conclusion holds.

This paper contributes to two strands of literature. First, we add to the literature on explaining the dispersion of analysts' forecasts. The literature documents that extreme negative events, like terrorist attacks and COVID-19, would lead to analysts' bias in forecasting, and they attribute the effect to changes in risk attitude or information lockdown

(Cuculiza et al., 2020; Gao et al., 2021; Xue, 2022; Zheng et al., 2022; Liang et al., 2022; Xu et al., 2021). Our work contributes to the literature by verifying the channel of attention distraction. Second, this study contributes to the literature on COVID-19's effects on various economic agents from the perspective of analysts (Awawdeh et al., 2021; Iqbal and Bilal, 2021; Ngo et al., 2021; Cao and Chou, 2022; Zeng et al., 2022; Duan and Lin, 2022; Lööf et al., 2022). Moreover, while our research question is close to Gao et al. (2021), we provide different conclusions by improving the measurement of the pandemic.

2. Data and Empirical Design

2.1. Data and sample

We obtain earnings forecasts issued by sell-side analysts and the basic information of brokers and analysts from the China Stock Market & Accounting Research (CSMAR). To identify the locations of analysts, we follow Jiang et al. (2016), Ho and Wu (2021), and Jiang et al. (2022), and use the provinces where analysts' branch offices locate as their locations. The historical information on middle- and high-risk areas are manually collected from the website of the State Council of China.

Our sample period covers all calendar months of 2020 and 2021. We exclude the first nationwide wave of the COVID-19 pandemic in China, which started in Wuhan in early 2020 and ended around April 2020. After that, the pandemic response level was reduced to level II, and the provincial governments took the decision-making power in formulating specific policies against the pandemic. Finally, we get 64,322 analyst-firm-month observations for our empirical tests.

2.2. Model and variables

Our baseline regression for testing the hypothesis is as follows:

$$DISPERSION_{k,i,t} = \beta_0 + \beta_1 COVID_{k,t} + \beta \boldsymbol{X} + \alpha_k + \eta_i + \delta_t + \varepsilon_{kit} \quad (1)$$

where *k*, *i*, and *t* indexes analyst, target firm, and calendar month, respectively. The dependent variable, *DISPERSION*, is the dispersion of analysts' forecasts to consensus one. We measure it with the absolute value of the difference between an analyst's earnings per share forecast on a target firm with the consensus forecast. The consensus forecast is the average value of the latest earnings forecasts issued by all analysts towards the same target firm within the same calendar month. The independent variable, *COVID*, is an indicator variable that equals one if a province has any middle or high-risk areas in a calendar month, and zero otherwise.

X is a vector of control variables. Following Lin et al. (2022a; 2022b; 2022c), Pan et al. (2022a; 2022b), Kong et al. (2020) and Chen et al. (2020), we include the following variables in the regression model: (1) *TARGETEXP*, which is the number of years that an analyst followed a target; (2) *FOLLOWCOMS*, measured as natural logarithm of the number of target firms an analyst following in a fiscal year; (3) *FOLLOWINDUS*, measured as natural logarithm of the number of target industries an analyst following in a fiscal year; (4) *GENERALEXP*, which is natural logarithm of an analyst's working experience (year); (5) *ALLSTAR*, measured as a dummy that equals one if an analyst is ranked as first to fifth in the institutional investors' ranking and zero otherwise; (6) *BROKERSIZE*, which is measured with natural logarithm of the number of active analysts for a broker in a fiscal year.

α_k, η_i, and δ_t are analyst, target firm, and calendar month indicator variables. All standard errors are adjusted for arbitrary heteroskedasticity and clustered by the analyst for error correlations. We winsorize all continuous variables at 1% and 99% to mitigate the influences of outliers. Table 1 summarizes the descriptive statistics.

[Insert Table 1 here]

3. Empirical Results

3.1. The basic effects

Table 2 presents the results from estimating equation (1). Column 1 includes the dependent variable, independent variable, and firm- and month-fixed effects. Column 2 adds analysts' and brokers' characteristics. Column 3 includes analyst indicator variables based on Column 2. All coefficients of *COVID* are significantly negative in Columns 1 to 3. Specifically, Column 3 indicates that *COVID* is negatively correlated with *DISPERSION*, with the coefficient estimated at -0.074, significant at the 1% level. The result is consistent with the hypothesis that the COVID-19 pandemic has a negative effect on analysts' forecast dispersion. In economic terms, the result in Column 3 indicates that the pandemic leads to a 17% decrease of analysts' forecast dispersion.

In terms of control variables, we find that the years an analyst following a target firm is negatively correlated with forecast dispersion. However, analysts' ranking is positively correlated with the dispersion of their forecasts.

[Insert Table 2 here]

3.2. Mechanism tests

As we discussed earlier, the negative effect of the COVID-19 pandemic on the dispersion of analysts' forecasts may be the result of a change in risk attitude (Vacca, 2020) or distraction of attention (Dong and Heo, 2014). We test these two possible channels in this section.

If the risk channel works in our baseline result, we could expect a more pronounced effect for the earlier wave of the pandemic because the attitude towards risk changes much when first facing the shock. Given so, we split the independent variable, *COVID*, in the equation (1) into two dummies, *COVID_FIRST*, which equals one for a province-year firstly experiencing the middle- or high-risk areas in our sample period, and *COVID_SUBSE*, which equals one for a province-year experiencing the subsequently appointed middle- or high-risk areas. We replace the variable *COVID* with these two new dummies and rerun the regression. Columns 1 and 2 of Table 3 report the result and show that both coefficients of the two new dummies are negative and significant. Moreover, the t-tests show that there is no significant difference between the coefficients of these two dummies. The result is inconsistent with the risk-averse explanation of our baseline results.

An alternative explanation of the basic result is the pandemic leads to analysts' attention distraction. If this channel work, an inference is that the number of forecasts issued by analysts will decrease after exposure to the pandemic. We construct a new sample with the structure of analyst-month, also a new dependent variable, *FORECASTNUM*, which is natural logarithm of the number of forecasts issued by an analyst in a calendar month. We rerun the regression and present the results in Columns 3 and 4 of Table 3. Both coefficients of *COVID* are significantly negative, indicating that the number of earnings forecast by analysts exposed to the pandemic decreased after the outbreak of COVID-19. The results support the channel of analysts' attention distraction.

[Insert Table 3 here]

3.3. DID analyses

To address potential endogeneity concerns, we conduct a staggered DID analysis by comparing the province exposed to the pandemic and not, before and after the exposure. We narrow the sample to a window 3-month before and after the time when a province appointed a middle- or high-risk area. We then construct a new variable, *COVID_DID*, which equals one for the months after a province was exposed to the pandemic and zero otherwise. We rerun the regression and the significantly negative coefficient of *COVID_DID* in Column 1 of Table 4 supports our conclusion. Column 2, Table 4 presents the dynamic analysis of the DID model, and our result holds.

[Insert Table 4 here]

3.4. Robustness tests

We conduct a series of tests to verify the robustness of our conclusion. First, we exclude analysts with locations in Beijing, Shanghai, Shenzhen, and Guangzhou, which have a large number of brokers and analysts. Column 1 of Table 5 presents the result, which is consistent with our conclusion. Second, we exclude target firms with less than 5 analysts following to make the with-firm comparison valid. We present the result in column 2 of Table 5, which supports our basic result again. Third, we measure the dispersion of analysts' forecasts by defining an indicator equaling one for dispersion larger than the median value and zero otherwise. We present it in Column 3 of Table 5 and find our conclusion holds. Fourth, we conduct a placebo test. Specifically, for each outbreak of the pandemic, we randomize the located province. There is no significant effect of the random pandemic on analyst forecast behavior. See Column 4 of Table 5 for the result. Fifth, we use propensity score matching to address the potential selection bias in analysts' forecast dispersion. Our conclusion is supported by the untabulated result.

[Insert Table 5 here]

3.5. Additional analyses

We are interested in whether the negative effect of COVID-19 on analysts' forecasting dispersion is a comprehensive result of two-side impacts. As discussed earlier, the pandemic can increase the dispersion of analysts' forecasts if the pandemic increases their pessimism (Cuculiza et al., 2020) or lockdown their access to information (Gao et al., 2021).

First, to verify the possibility of increasing pessimism, we test whether the effect of COVID-19 exists only in the pessimistic earnings forecasts. We replace the *DISPERSION* with *PESSIMISM*, which equals the absolute value of analyst dispersion for pessimistic forecasts (i.e., earnings forecast less than the consensus) and zero for optimistic ones. We construct the variable, *OPTIMISM*, with the same logic. However, Columns 1 and 2 of Table 6 show that both coefficients of *COVID* are significantly negative, against the possibility of increasing pessimism.

Second, if the channel of information lockdown works, the effect of COVID-19 would result in more divergent forecasts for opaque target firms. We separate the sample with different information transparent levels of target firms, which are measured with the absolute value of earnings management. We indeed find more pronounced pandemic effects between groups in opaque firms (Column 3), which is consistent with Gao et al. (2020) and indicates that our basic effect is a comprehensive impact of COVID-19.

[Insert Table 6 here]

4. Conclusion

The theoretical prediction of COVID-19's effect on analyst forecast behavior is two-sided and existing empirical studies have yet to reach a consensus. This paper provides evidence supporting the negative effect of the pandemic on analyst forecast dispersion. To illustrate underlying mechanisms, we verify the effect of the pandemic on analysts' efforts, which supports the explanation of attention distracted by COVID-19. We conduct a series of robustness tests and find our conclusion robust. This paper contributes to understanding the mechanism of extreme negative events' effect on analysts' forecast behavior, also the pandemic effect on economic agencies.

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Table 1. Descriptive Statistics

Variable	Mean	SD	P25	P50	P75	Obs
DISPERSION	0.433	0.537	0.143	0.270	0.493	64,322
PESSIMISM	0.421	0.521	0.137	0.265	0.485	64,322
OPTIMISM	0.004	0.024	0.000	0.000	0.000	64,322
COVID	0.018	0.132	0.000	0.000	0.000	64,322
TARGETEXP	1.755	0.706	1.000	2.000	2.000	64,322
FOLLOWCOMS	2.383	1.023	1.792	2.639	3.135	64,322
FOLLOWINDUS	2.152	0.559	1.792	2.197	2.565	64,322
GENERALEXP	2.648	0.852	2.063	2.699	3.372	64,322
ALLSTAR	0.026	0.158	0.000	0.000	0.000	64,322
BROKERSIZE	3.903	0.626	3.638	4.078	4.344	64,322

Table 2. The basic results

Dependent Variable:		***DISPERSION***	
	(1)	(2)	(3)
	Coefficient	Coefficient	Coefficient
	t-Statistic	*t*-Statistic	*t*-Statistic
COVID	-0.075***	-0.074***	-0.074***
	(-4.59)	(-4.54)	(-4.41)
TARGETEXP		-0.006**	-0.010***
		(-2.21)	(-3.66)
FOLLOWCOMS		-0.001	0.003
		(-0.26)	(0.57)
FOLLOWINDUS		0.000	-0.009
		(0.01)	(-0.77)
GENERALEXP		-0.001	-0.108***
		(-0.29)	(-7.38)
ALLSTAR		0.031***	0.058***
		(2.89)	(3.34)
BROKERSIZE		-0.003	-0.015
		(-1.08)	(-1.07)
Target Firm Fixed Effects	Control	Control	Control
Calendar Month Fixed Effects	Control	Control	Control
Analyst Fixed Effects	No	No	Control
Adj. R^2	0.773	0.773	0.781
Observations	64322	64322	64322

Table 3. Mechanism tests

Dependent Variable:	*DISPERSION*		*FORECASTNUM*	
	(1)	(2)	(1)	(2)
	Coefficient	Coefficient	Coefficient	Coefficient
	t-Statistic	*t*-Statistic	*t*-Statistic	*t*-Statistic
COVID_FIRST	-0.079***	-0.080***		
	(-4.64)	(-4.74)		
COVID_SUBSE	-0.098***	-0.099***		
	(-3.36)	(-3.31)		
COVID			-0.049*	-0.048*
			(-1.93)	(-1.87)
TARGETEXP		-0.010***		0.022**
		(-3.65)		(2.58)
FOLLOWCOMS		0.003		-0.024***
		(0.59)		(-2.73)
FOLLOWINDUS		-0.009		-0.154***
		(-0.82)		(-9.33)
GENERALEXP		-0.108***		0.024
		(-7.38)		(1.16)
ALLSTAR		0.058***		-0.021
		(3.38)		(-0.39)
BROKERSIZE		-0.016		-0.034*
		(-1.13)		(-1.85)
Target Firm Fixed Effects	Control	Control	Control	Control
Calendar Month Fixed Effects	Control	Control	Control	Control
Analyst Fixed Effects	Control	Control	Control	Control
Adj. R^2	0.780	0.781	0.360	0.368
Observations	64322	64322	12324	12324

Table 4. DID analyses

Dependent Variable:	***DISPERSION***	
	(1)	(2)
	Coefficient	Coefficient
	t-Statistic	*t*-Statistic
COVID_DID	-0.115**	
	(-2.48)	
COVID_DID[-2]		-0.016
		(-0.49)
COVID_DID[-1]		-0.066
		(-1.36)
COVID_DID[1]		-0.231***
		(-2.96)
COVID_DID[2]		-0.301***
		(-3.69)
COVID_DID[3]		-0.227***
		(-2.60)
TARGETEXP	-0.000	0.000
	(-0.04)	(0.01)
FOLLOWCOMS	0.003	0.002
	(0.20)	(0.17)
FOLLOWINDUS	-0.003	-0.003
	(-0.07)	(-0.09)
GENERALEXP	-0.216***	-0.214***
	(-7.48)	(-7.39)
BROKERSIZE	-0.019	-0.020
	(-0.36)	(-0.38)
Target Firm Fixed Effects	Control	Control
Calendar Month Fixed Effects	Control	Control
Analyst Fixed Effects	Control	Control
Adj. R^2	0.730	0.731
Observations	5170	5170

Table 5. Robustness tests

Dependent Variable:	***DISPERSION***	***DISPERSION***	***DISPERSION_D***	***DISPERSION***
	(1)	(2)	(1)	(2)
	Coefficient	Coefficient	Coefficient	Coefficient
	t-Statistic	*t*-Statistic	*t*-Statistic	*t*-Statistic
COVID	-0.059**	-0.075***	-0.036***	-0.020
	(-2.17)	(-2.70)	(-2.70)	(-0.94)
TARGETEXP	-0.014***	-0.011***	-0.015***	-0.009***
	(-3.78)	(-2.93)	(-4.61)	(-3.56)
FOLLOWCOMS	-0.003	0.001	0.002	0.002
	(-0.46)	(0.09)	(0.54)	(0.50)
FOLLOWINDUS	0.011	-0.000	0.002	-0.009
	(0.67)	(-0.01)	(0.15)	(-0.76)
GENERALEXP	-0.116***	-0.166***	-0.134***	-0.108***
	(-5.78)	(-8.78)	(-10.96)	(-7.32)
ALLSTAR	0.049**	0.070**	0.039***	0.058***
	(2.31)	(2.19)	(2.80)	(3.35)
BROKERSIZE	0.013	-0.015	-0.019	-0.015
	(0.60)	(-0.82)	(-1.37)	(-1.07)
Target Firm Fixed Effects	Control	Control	Control	Control
Calendar Month Fixed Effects	Control	Control	Control	Control
Analyst Fixed Effects	Control	Control	Control	Control
Adj. R^2	0.789	0.806	0.592	0.779
Observations	35814	36006	64322	64322

Table 6. Additional analyses

Dependent Variable:	***PESSIMISM***	***OPTIMISM***	***DISPERSION***	***DISPERSION***
	(1)	(2)	(1)	(2)
	Coefficient	Coefficient	Coefficient	Coefficient
	t-Statistic	*t*-Statistic	*t*-Statistic	*t*-Statistic
COVID	-0.064***	-0.002**	-0.079***	-0.057**
	(-3.96)	(-2.11)	(-3.47)	(-2.48)
TARGETEXP	-0.007***	-0.000	-0.013***	-0.008**
	(-2.84)	(-0.44)	(-3.24)	(-2.02)
FOLLOWCOMS	0.007	-0.001***	-0.050	-0.004
	(1.30)	(-2.70)	(-1.56)	(-0.41)
FOLLOWINDUS	-0.007	0.000	-0.008	0.001
	(-0.66)	(0.11)	(-0.41)	(0.05)
GENERALEXP	-0.129***	0.005***	-0.170***	-0.114***
	(-8.97)	(5.20)	(-5.30)	(-5.13)
ALLSTAR	0.059***	-0.001	0.052**	0.100***
	(3.12)	(-0.79)	(2.06)	(5.93)
BROKERSIZE	-0.012	0.000	-0.038	0.001
	(-0.97)	(0.25)	(-1.57)	(0.02)
Target Firm Fixed Effects	Control	Control	Control	Control
Calendar Month Fixed Effects	Control	Control	Control	Control
Analyst Fixed Effects	Control	Control	Control	Control
Adj. R^2	0.785	0.240	0.796	0.772
Observations	64322	64322	32238	32084

Author Statement

All the authors declare that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. There is no conflict of interest within our paper submission. And the manuscript is approved by all authors for publication.