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The effect of the COVID-19 pandemic on information disclosure: Evidence from China
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Using Chinese data, this study examines the effect of COVID-19 pandemic on tendencies and characteristics of information disclosure. Results show that, due to uncertainty caused by the pandemic, it is difficult to make earnings forecasts. Further, during the pandemic, forecast precision and timeliness decrease. The results remain unchanged under difference-in-difference (DiD) estimation. The findings of this paper extend existing studies on the economic consequences of COVID-19 pandemic and the influencing factors of information disclosure, providing implications for corporate managers, investors, and regulators.

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1. Introduction

COVID-19 is a once-in-a-century public health emergency that has been ongoing for more than two years. Previous studies have found that COVID-19 has significant influences on the macroeconomy and corporate behaviors, including GDP growth (Jena et al., 2021), monetary policy (Yilmazkuday, 2022), industrial output (Caggiano et al., 2020), guidance withdrawals (Hope et al., 2022), and investor sentiment (Liu et al., 2020). Due to the widespread and lasting effects of COVID-19, research on the economic consequences of the pandemic has attracted great attention and become increasingly important.

Abundant of existing studies have realized that environmental or political uncertainty has significant impact on information disclosure behaviors. But few studies have examined how pandemic uncertainty affects information disclosure willingness nor characteristics, where pandemic uncertainty may lead to uncertainties in all aspects. We aim to fill in this gap based on the context of COVID-19 pandemic in China.\textsuperscript{1}

In highly uncertain environment, we argue that it is more difficult for managers to issue any forecast or issue precise forecasts, mainly because of information unavailability. Kim et al. (2016) find that economic uncertainty makes management forecast more difficult, since forecast requires a comprehensive understanding of the current situation (Goodman et al., 2014). In this regard, we argue that the COVID-19 pandemic may cause a great deal of uncertainty in enterprises, and both the quantity and quality of useful information in making forecasts are scarce. Under such circumstance, it is more difficult for managers to forecast future earnings. Thus, management forecast willingness and frequency will both decrease during the pandemic.

Further, we also test whether forecast characteristics are influenced by pandemic uncertainty. We argue that forecast precision and timeliness will both decrease for two reasons. First, as the above analysis indicates, due to high information costs, pandemic uncertainty can increase the difficulty in predicting future earnings for managers. Therefore, it is hard for managers to make precise or timely forecasts under pandemic uncertainty. Second, managers tend not to make precise or timely earnings forecasts due to the considerations of potential negative effects in the capital market. Kim and Verrecchia (1991) and Li and Zhang (2015) find that vague forecasts can stabilize a company’s stock price. Stock prices are more volatile (Xu et al., 2021) under uncertainty period, where management has strong incentives to stabilize or increase share prices (Li and Zhang, 2015). Moreover, to avoid dismissal risk due to delivering wrong information, management may delay their forecasts when they lack information under uncertainty (Lee et al., 2012; Kim et al., 2016). In this sense,
we predict that managers tend to make less precise and timely forecasts during COVID-19 pandemic.

Our study contributes to the existing literature in at least three respects. First and foremost, we are among the few researches, if not the first, to provide evidence that pandemic uncertainty affects corporate information disclosure. Hope et al. (2022) find that COVID-19 pandemic could affect management forecasts withdrawal. However, they do not test the results of disclosure tendency or characteristics. We extend this line of research. Second, we extend existing studies on the influencing factors of information disclosure. Third, it is crucial to study the economic consequences of COVID-19. Using international data, Arteaga-Garavito et al. (2020) show that medical announcements and social media information about COVID-19 have a significant impact on financial markets. Our findings enrich this strand of study by providing evidence about how COVID-19 affects corporate information disclosure.

The remaining paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the empirical results. Section 4 concludes the study.

2. Data and methodology

2.1. Data and sample

We select the quarterly data of Chinese listed companies from the first quarter of 2019 to the fourth quarter of 2020 as the sample. The data in baseline regressions are from the China Stock Market & Accounting Research (CSMAR) database and Wind database.

We filter the data as follows: (i) We exclude companies in the financial industry or with a status of ST or “ST;” (ii) in order to investigate the motivation of corporate managers, we exclude mandatory disclosure, including “substantial increase”, “substantial decrease”, “turning loss into profit”, “continued loss”, and “turning profit into loss”; (iii) we exclude companies with forecast date later than the quarterly report date; (iv) we exclude samples with missing variables. After the above processes, the final sample contains 19,583 firm-quarter observations.

2.2. Methodology

We use Eq. (1) to test the impact of the pandemic on information disclosure. Management forecast is a commonly used measure to proxy for information disclosure (Park et al., 2019). In Eq. (1), the dependent variable MF denotes the forecast tendency and characteristics. For management forecast tendencies, MF represents: (i) the quarterly management forecast indicator (Disclosure), which equals one if the company provides at least one quarterly management forecast, and zero otherwise; and (ii) management forecast frequency (Frequency), which equals the number of management forecasts within a quarter (Zhou et al., 2017; Park et al., 2019). Concerning the characteristics of management forecasts, MF represents: (i) the forecast precision is measured by the management forecast range (Range), which equals the width of forecasts, scaled by the absolute value of the forecast mid-point (Cheng et al., 2013); and (ii) the timeliness of the management forecast is measured by the management forecast horizon (Horizon), which equals the logarithm of the interval days between the release date of the forecast and the quarterly report plus one (Kim et al., 2016).

Moreover, the explanatory variable used in Eq. (1) is the COVID-19 pandemic (Pandemic), which equals one if the quarter falls in the pandemic period (year >= 2020), and zero otherwise (WHO, 2020). We include a series of control variables, as shown in Appendix. We control for industry × year-quarter fixed effects (Park et al., 2019) in order to mitigate concerns that a time-trend, time-varying industry characteristic, or economy-wide shocks affect the relationship between the pandemic and management forecasts. We also control for firm-fixed effects to eliminate unobservable firm-level influencing factors.

3. Empirical results

3.1. Summary statistics

Table 1 presents the summary statistics of our sample of 19,583 firm-quarter observations, including 3440 firm-quarter observations with voluntary management forecasts. The mean values of Disclosure and Frequency are 0.176 and 0.177, respectively, suggesting that about 17.6% of Chinese listed companies have issued quarterly management forecasts, and some of them issued more than once. The mean value of Pandemic is 0.490, suggesting that the samples from before and after the pandemic are relatively balanced.

3.2. The impact of COVID-19 on management forecast tendencies

The regression results regarding the COVID-19 pandemic and management forecast tendencies are shown in Table 2. In Column (1), the coefficient of Pandemic is -0.103 (t = -14.943), which is significant at 1%. It preliminarily verifies that COVID-19 has a negative effect on forecast willingness. In Column (2), the results remain unchanged when adding controls (coefficient = -0.071, t = -10.253). In terms of economic magnitude, compared with non-pandemic periods, forecast willingness decreases about 7.1% during the pandemic.

Additionally, the coefficient of Pandemic in Column (3) is -0.103 (t = -14.752) and in Column (4) is -0.071 (t = -10.132). Both are significant at the 1% level. These results indicate that management forecast frequencies also decrease during the pandemic. Overall, the results in Table 2 suggest that the COVID-19 pandemic has a negative effect on voluntary information disclosure tendencies.
Table 1
Summary statistics.

| Variables  | Obs  | SD     | Mean   | P25   | P50   | P75   |
|------------|------|--------|--------|-------|-------|-------|
| Disclosure | 19583| 0.381  | 0.176  | 0     | 0     | 0     |
| Frequency  | 19583| 0.386  | 0.177  | 0     | 0     | 0     |
| Range      | 3440 | 0.126  | 0.190  | 0.100 | 0.165 | 0.245 |
| Horizon    | 3440 | 0.753  | 3.547  | 2.833 | 3.638 | 4.234 |
| Pandemic   | 19583| 0.500  | 0.490  | 0     | 0     | 1     |
| SIZE       | 19583| 1.387  | 24.740 | 21.472| 22.822| 23.226|
| LEV        | 19583| 0.197  | 0.417  | 0.261 | 0.408 | 0.561 |
| SD_ROA     | 19583| 0.023  | 0.028  | 0.014 | 0.022 | 0.035 |
| SalesG     | 19583| 0.558  | 0.138  | −0.142| 0.048 | 0.267 |
| Age        | 19583| 0.857  | 4.638  | 3.912 | 4.745 | 5.438 |
| TOP5       | 19583| 21.368 | 0.385  | 0.201 | 0.383 | 0.550 |
| HHI        | 19583| 0.094  | 0.091  | 0.037 | 0.067 | 0.113 |
| BoardSize  | 19583| 0.197  | 2.113  | 1.946 | 2.197 | 2.197 |
| Inst       | 19583| 0.251  | 0.430  | −0.142| 0.048 | 0.267 |
| Coverage   | 19583| 1.271  | 1.269  | 0     | 1.099 | 2.303 |
| Audit      | 19583| 0.190  | 0.962  | 1     | 1     | 1     |
| Loss       | 19583| 0.496  | 0.559  | 0     | 1     | 1     |

Table 2
The Influence of COVID-19 Pandemic on Management Forecast Tendency.

|                         | (1) | (2) | (3) | (4) |
|-------------------------|-----|-----|-----|-----|
| Dependent               | Disclosure | Disclosure | Frequency | Frequency |
| Pandemic                | −0.103*** | −0.071*** | −0.103*** | −0.071*** |
|                         | (−14.943) | (−10.253) | (−14.752) | (−10.132) |
| SIZE                    | 0.089*** | 0.091*** | (2.850) | (2.883) |
| LEV                     | −0.102 | −0.103 | (−1.191) | (−1.186) |
| BTM                     | 0.012** | 0.012** | (2.223) | (2.222) |
| SD_ROA                  | −0.244 | −0.285 | (−0.793) | (−0.932) |
| SalesG                  | −0.004 | −0.003 | (−0.863) | (−0.741) |
| Age                     | −0.288*** | −0.286*** | (−8.290) | (−8.161) |
| TOP5                    | 0.127*** | 0.128*** | (4.553) | (4.579) |
| HHI                     | 0.107 | 0.091 | (0.793) | (0.673) |
| BoardSize               | −0.021 | −0.020 | (−0.334) | (−0.317) |
| Inst                    | 0.220** | 0.221** | (2.221) | (2.221) |
| Coverage                | −0.000 | 0.000 | (−0.042) | (0.023) |
| Audit                   | 0.026 | 0.026 | (0.693) | (0.696) |
| Loss                    | 0.010** | 0.009* | (2.090) | (1.887) |
| _cons                   | 0.225*** | 0.224*** | (6.709) | (6.678) |
| Indus*Quarter FE        | YES | YES | YES | YES |
| Firm FE                 | YES | YES | YES | YES |

N  | 19583 | 19582 | 19583 | 19582 |
| adj. R² | 0.508 | 0.515 | 0.501 | 0.508 |

Columns (1) and (2) use management forecast dummy (Disclosure) as the dependent variable. The forecast frequency (Frequency) is used in Columns (3) and (4). Moreover, Columns (1) and (3) are regressed with just the Indus-Quarter fixed effect and the firm fixed effect, but without any control variables. Columns (2) and (4) further add control variables in the regressions. t statistics are reported in parentheses. * p < .10, ** p < 0.05, *** p < 0.01.

3.3. The impact of COVID-19 on management forecast characteristics

In this section, we further test the relationship between COVID-19 and management forecast characteristics. The regression results are reported in Table 3. We use Heckman two stage model to alleviate potential sample selection issue (Heckman, 1979). In Column (2), the coefficient of Pandemic is 0.221 (t = 3.292) and is significant at 1% level, indicating that, compared with non-pandemic period, management forecast ranges
In this section, we further identify the treatment (control) sample and use a DiD model to conduct robustness tests. We set treatment firms as those severely affected by the pandemic. Treat measures whether the location of the firm is severely affected by the COVID-19 pandemic, which equals one if the province of the firm is in the top 50% of cumulative confirmed cases in the sample period, and zero otherwise.

Table 4 presents the results regressing management forecast tendencies (characteristics) on Treat * Pandemic and all of the control variables. We can see that the coefficients of Treat * Pandemic are significantly negative for forecast tendencies (Disclosure and Frequency) and timeliness (Horizon), and are significantly positive for forecast range (Range). The results further support our conclusions.

3.4. Robustness check

3.4.1. DiD robustness tests

In this section, we further identify the treatment (control) sample and use a DiD model to conduct robustness tests. We set treatment firms as those severely affected by the pandemic. Treat measures whether the location of the firm is severely affected by the COVID-19 pandemic, which equals one if the province of the firm is in the top 50% of cumulative confirmed cases in the sample period, and zero otherwise.

Table 4 presents the results regressing management forecast tendencies (characteristics) on Treat * Pandemic and all of the control variables. We can see that the coefficients of Treat * Pandemic are significantly negative for forecast tendencies (Disclosure and Frequency) and timeliness (Horizon), and are significantly positive for forecast range (Range). The results further support our conclusions.

Since we can only obtain forecast characteristics data with disclosure, sample selection bias may exist. In Column (1) of Table 3, we regress the disclosure dummy variable (Disclosure) to all of the independent variables using the full sample and obtain the inverse mills ratio (IMR). Columns (2) and (3) show the regression results based on Eq. (1) after adding the IMR obtained from the first-stage regression. The dependent variables in Columns (2) and (3) are Range and Horizon, respectively. t statistics are reported in parentheses. * p < .10, ** p < .05, *** p < .01.

are likely to increase during the pandemic. The coefficient of Pandemic in Column (3) is −2.333 (t = −4.956). It shows that forecasts are less timely during pandemic period. Overall, the results about forecast characteristics are in accordance with our predictions.

3.4. Robustness check

3.4.2. Parallel trend test

The premise of the DiD model used in this study is that the treatment group and the control group have a common trend before the outbreak of COVID-19. The difference occurs only after the pandemic outbreak. The parallel trend test is presented in Figs. 1 and 2. Specifically, Fig. 1 shows the difference in Disclosure between the treatment and control groups from three quarters before the outbreak of COVID-19 (2019 Q2–Q4; namely, Before3, Before2, and Before1) to three quarters after (2020 Q1–Q3; namely, Post1, Post2, and Post3), and Fig. 2 shows the difference in Frequency.

In Figs. 1 and 2, we can see that, before the COVID-19 pandemic, the treatment and control samples do not exhibit any differences in their management forecast tendencies. The management forecast willingness and frequency decrease just after the pandemic. This finding is consistent with our predictions that pandemic uncertainty could decrease corporate information disclosure tendencies.

4. Conclusion

Under the context of COVID-19 pandemic, abundant of existing studies have studied its effect on macro-economy and some firm behaviors. However, few studies have focused on the relationship between pandemic uncertainty and corporate information disclosure. Using management forecast tendencies and characteristics as proxies, we find that, during pandemic period, firms decrease both forecast tendencies and quality. The
results of this study extend existing research on the economic consequences of the COVID-19 pandemic and the influencing factors of information disclosure behaviors. This study provides certain implications for corporate managers, investors, financial intermediaries, and regulators. We suggest regulators encourage companies to improve their information transparency and quality, especially during uncertain times.

Appendix

See Table A.1.

Table A.1

| Variables definitions. | Definitions |
|------------------------|-------------|
| Disclosure             | Management forecast dummy. If it equals one if the company provides at least one quarterly management forecast, otherwise zero. |
| Frequency              | Management forecast frequency. It equals the number of management forecasts in a quarter. |
| Range                  | Management forecast range. It equals the width of range forecasts, scaled by the absolute value of the forecast mid-point. |
| Horizon                | Management forecast horizon (or timeliness). It equals the logarithm value of the interval days between the release date of forecast and quarterly report plus one. |
| Pandemic               | COVID–19 pandemic dummy, which equals one if the quarter falls in the pandemic period (year >= 2020), otherwise zero. |
| Treat                  | Treatment firm dummy, which measures whether the location of the firm is severely affected by the COVID–19 pandemic. It is a dummy variable which equals one if the province of the firm is of top 50% cumulative confirmed cases in sample period, otherwise zero. |
| SIZE                   | Firm size, which equals the logarithm of the book value of total assets. |
| LEV                    | Leverage, which equals total debt divided by total assets. |
| BTM                    | Book-to-market ratio, which equals the book value of equity divided by the market value of equity at the end of the quarter. |
| SD_ROA                 | ROA volatility, which equals the standard deviation of return on assets divided by total assets in the previous four quarters. |
| SalesG                 | The growth of sales, which equals (operating income in the current quarter–operating income in last quarter)/operating income in last quarter. |

Table A.1 (continued).

| Variables               | Definitions |
|------------------------|-------------|
| Age                    | The logarithm value of firm age (in months). Ownership concentration, which equals quarterly share ownership percentage of the top five shareholders. |
| TOP5                   | The degree of market competition, measured as Herfindahl–Hirschman Index, which is the sum square of the market share of all firms within each industry-quarter. |
| HHI                    | Board size, which equals the logarithm value of the number of board members plus one. |
| BoardSize              | Institution holdings, which equals shares of percentage held by institutional investors. |
| Inst                   | Audit opinion indicator, which equals one if the audit opinion is a standard unqualified opinion, otherwise zero. |
| Coverage               | Loss indicator, which equals one if the company’s net profit is greater than zero, otherwise zero. |
| Indus*Quarter FE       | Interactive fixed effects of industry and year-quarter dummies. |
| Firm FE                | Firm fixed effect. |

References

Angrist, J.D., Pischke, J.S., 2009. Instrumental variables in action: Sometimes you get what you need. In: Mostly Harmless Econometrics: An Empiricist’s Companion. pp. 113–220. http://dx.doi.org/10.1515/9781400829828.

Arteaga-Garavito, M.J., Croce, M.M.M., Farroni, P., et al., 2020. When the markets get COVID: Contagion, viruses, and information diffusion. http://dx.doi.org/10.2139/ssrn.3560147.

Caggiano, G., Castelnuovo, E., Kima, R., 2020. The global effects of Covid-19-induced uncertainty. Econ. Lett. 194, 109392. http://dx.doi.org/10.1016/j.econlet.2020.109392.

Chen, S., Matsumoto, D., Rajgopal, S., 2011. Is silence golden? An empirical analysis of firms that stop giving quarterly earnings guidance. J. Account. Econ. 51 (1–2), 134–150. http://dx.doi.org/10.1016/j.jaccheco.2010.10.005.

Cheng, Q., Luo, T., Yue, H., 2013. Managerial incentives and management forecast precision. Account. Rev. 88 (5), 1575–1602. http://dx.doi.org/10.2308/accr-50506.

Goodman, T.H., Neamtiu, M., Shroff, N., White, H.D., 2014. Management forecast quality and capital investment decisions. Account. Rev. 89 (1), 331–365. http://dx.doi.org/10.2308/accr-50575.

Hope, O.K., Li, C., Ma, M.S., et al., 2022. Is silence golden sometimes? Management guidance withdrawals during the COVID-19 pandemic. Rev. Account. Stud. http://dx.doi.org/10.2139/ssrn.4024379.

Jena, P.R., Majhi, R., Kalli, R., Managi, S., Majhi, B., 2021. Impact of COVID–19 on GDP of major economies: Application of the artificial neural network econometric model. Account. Horizons 30 (1), 157–172. http://dx.doi.org/10.2308/ach-51311.

Kim, K., Pandit, S. (Shail), Wasley, C.E., 2016. Macroeconomic uncertainty and management earnings forecasts. Account. Horizons 30 (1), 157–172. http://dx.doi.org/10.2308/ach-51311.

Kim, O., Verrecchia, R.E., 1991. Trading volume and price reactions to public announcements. J. Account. Res. 29 (2), 302–321. http://dx.doi.org/10.2307/2491051.
Kitagawa, N., 2021. Macroeconomic uncertainty and management forecast accuracy. J. Contemp. Account. Econ. 17 (3), 100281. http://dx.doi.org/10.1016/j.jcae.2021.100281.

Lee, S., Matsunaga, S.R., Park, C.W., 2012. Management forecast accuracy and CEO turnover. Account. Rev. 87 (6), 2095–2122. http://dx.doi.org/10.2308/accr-50220.

Li, Y., Zhang, L., 2015. Short selling pressure, stock price behavior, and management forecast precision: Evidence from a natural experiment. J. Account. Res. 53 (1), 79–117. http://dx.doi.org/10.1111/1475-679X.12068.

Liu, H., Manzoor, A., Wang, C., Zhang, L., Manzoor, Z., 2020. The COVID-19 outbreak and affected countries’ stock markets response. Int. J. Environ. Res. Public Health 17 (8), 2800. http://dx.doi.org/10.3390/ijerph17082800.

Park, J., Sani, J., Shroff, N., White, H., 2019. Disclosure incentives when competing firms have common ownership. J. Account. Econ. 67 (2–3), 387–415. http://dx.doi.org/10.1016/j.jacceco.2019.02.001.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA.

Xu, W., Li, A., Wei, L., 2021. The impact of COVID-19 on China’s capital market and major industry sectors. Procedia Comput. Sci. 199, 87–94. http://dx.doi.org/10.1016/j.procs.2022.01.011.

Yilmazkuday, H., 2022. COVID-19 and monetary policy with zero bounds: A cross-country investigation. Finance Res. Lett. 44, 102103. http://dx.doi.org/10.1016/j.ijerph.2021.102103.

Zhou, K., Jiang, S., Ma, Z., 2017. Political uncertainty and voluntary management earnings forecasts. China J. Account. Stud. 5 (2), 256–273. http://dx.doi.org/10.1080/21607213.2017.1341751.