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Economic policy uncertainty, COVID-19 lockdown, and firm-level volatility: Evidence from China

Jianlei Yang, Chunpeng Yang*

Finance and Security Center, School of Economics and Commerce, South China University of Technology, Guangzhou, China; 510006

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ABSTRACT

To explain how firm-level volatility responds to the COVID-19 pandemic shock through the economic policy uncertainty (EPU) channel, we examine the two-dimension variations of stock volatility under the impact of COVID-19 pandemic and two types of EPU: measured by comprehensive newspapers news and financial newspapers news. The results, based on a difference in difference (DID) estimation, suggest a significant additional increase in the volatility of stocks with a higher degree of sensitivity to EPU after the announcement of the COVID-19 pandemic lockdown. Moreover, this effect is most pronounced for consumer, less-profitable, and high leverage stocks. Further multi-period analyses indicate that the impact of EPU associated with pandemic takes effect at the time of lockdown announcement and persist for a short-term trend.

1. Introduction

Since the sudden outbreak and worldwide spread of the novel coronavirus (COVID-19) pandemic in 2020, the global economy has witnessed severe turbulence and considerable losses. To avoid the spread of COVID-19, the Chinese government has imposed a travel lockdown in Wuhan, the industrial city at the epicenter of the outbreak. On 23 January 2020, all public transportation was halted in Wuhan and nearby cities, which are together home to more than nine million residents. Subsequently, the economy had been stagnant, and the stock markets responded with extreme shock. According to some stylized facts for Chinese stock markets presented in this study, the average daily volatility of CSI300 constituent stocks increased over 31% in the two months after the pandemic lockdown. Meanwhile, we have discovered an increase in the news-based Chinese economic policy uncertainty (EPU) indexes after the pandemic outbreak, which is consistent with the finding of Altig et al. (2020). Motivated by this series of evidence, this paper aims to shed light on how pandemic shocks like the destructive COVID-19 outbreak can amplify firm-level volatility through EPU channels.

Recently, a rapidly growing body of empirical studies has examined the impact of COVID-19 pandemic on stock markets, and these studies can be roughly classified into two types. Firstly, based on event study methodology, Huo and Qiu (2020) find the existence of abnormal return reversals at both the industry and the firm levels during COVID-19 pandemic; Sun et al. (2020) reveal that COVID-19-related news and economic-related announcements associated with the outbreak pose positive and significant effects on five international stock markets' medical portfolios; Narayan et al. (2020) show that lockdown, travel bans, and economic stimulus packages all

* Corresponding author.
E-mail address: chpyang_scut@outlook.com (C. Yang).

1 The CSI300 is a capitalization-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Shanghai Stock Exchange and the Shenzhen Stock Exchange.

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had a positive effect on the G7 stock markets. He et al. (2020) test the COVID-19's impact on stock prices across different sectors of China and found that the pandemic hit the traditional industries negatively and more seriously but created opportunities for the development of high-tech industries. Secondly, using mortality or morbidity as independent variables, Ashraf (2020) shows that stock market returns declined as the number of confirmed cases increased; Onali (2020) provides evidence that changes in the number of cases and deaths in the U.S. and six other countries majorly affected by the Covid-19 crisis positively impact the conditional heteroskedasticity of the Dow Jones and S&P500 returns; Yilmazkuday (2020) suggests that having 1% of an increase in cumulative daily COVID-19 cases in the U.S. results in about 0.01% of a cumulative reduction in the S&P 500 Index after one day and about 0.03% of a reduction after one month. However, the chain effect of a pandemic shock could be multidimensional, manifesting through the government's policy response, firms' risk exposure, and investors' risk expectations. In addition to focusing on pandemic crises' direct effect, we believe that it is critical to examine whether EPU is a transmission channel through which the COVID-19 pandemic can affect stock volatility.

EPU has been documented as a determinant of stock volatility (e.g., Liu and Zhang, 2015; Baker et al., 2016; Li et al., 2020; Shen et al., 2020). As essential empirical evidence among the numerous studies focusing on the impact of the COVID-19 pandemic, Altig et al. (2020) reveal that all economic policy uncertainty (EPU) indicators, including implied stock market volatility, newspaper-based EPU index, Twitter chatter about EPU, subjective uncertainty about business growth, forecaster disagreement about future GDP growth, and a model-based measure of macro uncertainty, reached its highest point as recorded during the COVID-19 pandemic. Specifically, this study leaves several economic implications of such effects for further investigation. Therefore, it leads to our paper's primary purpose: to check whether the record high of EPU level could be associated with the surge in stock volatility after the pandemic outbreak. It is particularly noteworthy that our research focuses on the effects of two types of EPU: measured by comprehensive newspapers news and financial newspapers news. Huang and Luk (2020) develop a comprehensive EPU index of China based on newspapers covering general interest news. However, the existing comprehensive EPU index loses sight of information from financial newspapers. As a complementary measure of EPU, this study constructs a relatively specialized financial EPU index based on 15 leading financial newspapers of mainland China. Indeed, Yang et al. (2020) find consistent evidence that the daily financial EPU index has the highest explanatory power for volatility in the Chinese stock markets than other existing EPU indexes.

This literature highlights how firm-level volatility varies in the EPU exposure dimension and time dimension by introducing exogenous pandemic shocks. Hence, it can help to better understand the role of EPU in explaining stock volatility caused by tail risks of disaster events other than normal market frictions. Furthermore, the study on the firm-specific characters and dynamic trend of such two-dimension effects has been underexplored.

Essentially, when a novel, tremendous shock hits with great suddenness, both the intensity and the timeliness of policy responses would become highly uncertain. For instance, the Chinese central government has suspended enterprise at the beginning of the pandemic outbreak. Considering that the situation continues to be fluid, the main challenge for the resolution of regular activity and the full effect of supply chain disruptions were unclear. Since January 2020, local governments have issued new emergency measures on a sporadic basis that govern salary payment standards, which added a burden to the enterprises. Moreover, in January and February, the current monetary policy has been altered and adjusted frequently. Consequently, with an increase in EPU, investors' perceptions of unexpected risk would be enhanced and inconstant, leading to higher stock volatility. According to the general equilibrium asset pricing model proposed by Pastor and Veronesi (2012), the EPU affects asset price by raising the volatility of the stochastic discount factor. Pastor and Veronesi (2013) put forward the theory and prove that the impact of EPU on volatility should be more substantial when the economy is weaker. More importantly, the asset pricing implications of non-financial shock, demand contractions, and expansion in fiscal policy have been emphasized in the context of the spread of Covid-19 (Caballero and Simsek, 2020). Besides, Pastor and Veronesi (2012) suggest that different firms have different exposures to EPU and thus are impacted differently by EPU. Their argument implies that the firm-level stock volatility could also differ enormously in reaction to the EPU change due to pandemics. On the one hand, negative policies such as regional lockdown lower expected returns for firms with high exposures to consumer products, including catering services, tourism, and traditional retail, directly via contraction in demand linkages. On the other hand, companies with low profit and high leverage suffer the disadvantage of lack resiliency and would be in a worse position to undertake new investments when economic stimulus policies are released.

Based on the aforementioned theoretical framework, we conjecture that the COVID-19 pandemic has greatly affected stock volatility, with the critical channel being EPU shock. According to our descriptive analysis (as shown in Fig. 2), the dynamic trend for high and low EPU-sensitive stocks deviate obviously from each other just after the COVID-19 pandemic lockdown announcement. Specifically, we have three main hypotheses as follows. First, stocks with a higher degree of sensitivity to EPU tend to have a higher tendency of volatility increase after the outbreak; Second, several firm-specific characteristics, including main business, profitability, and leverage ratio, would make the volatility of some stocks more sensitive to EPU changes due to pandemics. Third, the two-dimension effects of COVID-19 pandemic and EPU are likely to be persistent in the short term. In the Hypothesis development section, we provide theoretical frameworks that formalize the above intuitional arguments.

We test our hypotheses by matching two types of daily EPU index, measured by comprehensive newspapers news and financial

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2 The statement is issued by China's Development and Reform Commission. Official websites: https://www.ndrc.gov.cn.

3 Since January 6, 2020, the People's Bank of China (PBOC) has been cutting the deposit reserve ratio of financial institutions by 0.5%. On February 3, the PBOC released 1.2 trillion yuan (a record in a single day) through its open-market operations. On February 4, PBOC conducted a reverse repurchase (repo) agreement worth 500 billion yuan. According to data released by PBOC, new loans are 7.1 trillion in the first quarter of 2020, increasing 22% from a year earlier. Data reference: http://www.pbc.gov.cn.
newspaper news with the corresponding individual stock volatility, and examining the two-dimension variations of stock volatility under the impact of COVID-19 pandemic and EPU. Specifically, we collect CSI300 constituent stock data spanning from 25 November 2019 to 23 March 2020. Then, we use the difference-in-difference (DID) estimation method to explore the two-dimension variations of stock volatility, sensitivity level to EPU (i.e., high relative to low), and time (i.e., before and after the COVID-19 pandemic lockdown).

As we expected, controlling for lagged volatility, stock fixed-effects, and prior known determinants of volatility, our empirical analysis has uncovered a significant additional increase in the volatility of stocks with a higher degree of sensitivity to EPU after the announcement of the COVID-19 pandemic lockdown. This effect is most pronounced for consumer, less-profitable, and high leverage stocks. Moreover, the dynamic marginal evolution of the two-dimension variations of stock volatility is discontinuous in the whole sampling interval but is stable during the short period after the pandemic outbreak. In addition, our empirical results are still valid after adopting alternative measures of volatility or replacing the treatment variable by randomly assigning EPU to stocks. Overall, these results confirm the crucial role of EPU as an effective transmission channel through which the COVID-19 pandemic can affect stock volatility. Further, these results have significant implications on financial market participants, who should realize and utilize the EPU channel to manage financial risks during pandemic crises.

This study contributes to the literature in several ways. First, we document novel two-dimension variations of stock volatility under the impact of COVID-19 pandemic and EPU in the Chinese stock markets. Whereas many empirical investigations directly examine how stock markets respond to the COVID-19 pandemic shock. (e.g., Baker et al., 2020; Huo and Qiu, 2020; Narayan et al., 2020; Yilmazkuday, 2020; Zhang et al., 2020). Second, we contribute to a rapidly growing body of empirical studies that focus on the connection between the EPU index and stock markets. For example, Brogaard and Detzel (2015) provide empirical evidence that EPU commands a negative equity premium. Liu and Zhang (2015) suggest that higher EPU leads to significant increases in market volatility. Using firm-level data, Baker et al. (2016) find that EPU raises stock price volatility in policy-sensitive sectors. Li et al. (2020) show that Up and down EPU can lead to substantially high stock market volatility in China. Shen et al. (2020) find that EPU negatively affects stock price synchronicity in China. Beyond these studies, we consider the effects of two types of EPU measured by comprehensive newspaper news and financial newspaper news on the stock volatility due to COVID-19 pandemic. This study is important since we provide empirical evidence that EPU is a critical channel of propagating violent non-financial shocks like the pandemic outbreak. Third, we further show that heterogeneity in the two-dimension effect of EPU and COVID-19 pandemic on individual stock volatility originates from three sources: the industry, the profitability, and the leverage ratio characteristics. Specifically, the two-dimension effect is most pronounced for consumer, less-profitable, and high leverage stocks. Fourth, by adopting a multi-period DID approach, we provide evidence of dynamic variations in the short-term effects of EPU and COVID-19 on stock market volatility. Additionally, our results are robust to several alternative volatility measures and placebo tests.

The rest of our paper is organized as follows. Section 2 outlines the theories and sets the hypothesis. Section 3 describes data and models. Section 4 summarizes empirical findings. Concluding remarks are included in Section 5.

2. Hypothesis development

In this paper, we test whether EPU is a transmission channel through which the COVID-19 pandemic can affect stock volatility. Specifically, the empirical research is built around the following three assumptions.

Firstly, based on the theoretical framework of Pastor and Veronesi (2012, 2013), we propose a simplified model that illustrates the causal mechanisms of the increasing volatility of stocks with a higher degree of sensitivity to EPU under the impact of pandemics.

We consider an economy with a finite horizon \([0,T]\) and a continuum of firms \(i \in [0, 1]\). The firms are financed entirely through equity, which means the firm’s capital \(B_t^i\) is equal to its book value. All firms initially employ an equal amount of capital \(B_0^i = 1\). Therefore, firm \(i\)’s capital evolves according to the equation: \(dB_t^i = B_{tg} \text{d}t\). We introduce the random variable of economic policy effect \(g_t\) into the following firm profitability process:

\[
dp_t^i = (\mu + g_t)\text{d}t + \sigma dZ_t + \sigma_t dZ_t^i
\]  

(1)

where \(\mu\) is the mean of the profitability process, \(\sigma\) is a general drift item, and \(\sigma_t\) is a drift that is specific to firm \(i\). \(Z_t\) and \(Z_t^i\) are two independent Brownian motions. The economic policy effect \(g_t\) conforms to a normal distribution: \(g_t \sim N(0, \sigma_g^2)\), and \(\sigma_g\) denotes economic policy uncertainty.

The pandemic outbreak begins at an exogenously given time \(\tau\), and the government decided to respond with policy changes. Assuming that no cost effects exist, the utility function of government policymaking is given by:

\[
u(W_T^i) = (W_T^i)^{1-\tau}(1-\gamma)^{-\tau}
\]  

(2)

where \(\gamma > 1\) is the risk aversion coefficient, \(W_T^i\) is the terminal wealth of firm \(i\), and In equilibrium, the terminal wealth \(W_T^i\) equals book value \(B_T^i\).

The market value of stock \(i\) is given by the stochastic discount model:

\[
M_T^i = E \left[ \frac{\pi_T B_T^i}{\pi_T} \right]
\]  

(3)

and the discount factor at time \(t\) is given by:

\[
\gamma_t = \frac{\pi_t B_t^i}{\pi_T B_T^i} \left( \frac{\pi_T B_T^i}{\pi_t B_t^i} \right)^{1-\tau}
\]  

(4)

where \(\pi_t\) is the probability that events occurring at time \(t\) will not disrupt the economic system.
\begin{equation}
\pi_t = \lambda^{-1} E[B_t^u]
\end{equation}

where $\lambda$ is the Lagrange multiplier from the utility maximization problem of the representative investor. According to the results of Pástor and Veronesi (2012, 2013), the stochastic discount factor could be expressed in the following random process:

\begin{equation}
\frac{d\pi_t}{\pi_t} = -\sigma_d d\tilde{Z}_t.
\end{equation}

For $t > \tau$, the volatility of the stochastic discount factor is given by:

\begin{equation}
\sigma_v = \gamma \left[ \sigma + (T-\tau)\sigma^2 \sigma^{-1} \right]
\end{equation}

From Eqs. (3) to (5), the return process for stock $i$ is given by:

\begin{equation}
\frac{dM_t^i}{M_t^i} = \mu_d dt + \sigma_d d\tilde{Z}_t + \sigma_1 dZ_t
\end{equation}

here, we focus on the volatility of the stock return. For $t > \tau$, we have:

\begin{equation}
\sigma_M = \sigma + (T-\tau)\sigma^2 \sigma^{-1}.
\end{equation}

We thus conclude from Eqs. (6), (8) that in the context of exogenous pandemic shocks, the theoretical model implies a positive relationship between economic policy uncertainty and stock volatility.

**Hypothesis 1.** Stocks with a higher degree of sensitivity to EPU tend to have higher volatility increase after the outbreak.

Moreover, we are particularly interested in further assessing the impact of EPU due to COVID-19 pandemic on volatility across stock portfolios of different firm characteristics, including firms’ main business, profitability, and leverage ratio. Therefore, to set the assumption concretely, we build a theoretical framework of how firms operations are affected by EPU due to pandemic shocks in Fig. 1, as follows:

The recent Covid-19 pandemic has an important impact on overall EPU, leading to a surge in firm-level volatility. As shown in Fig. 1, we consider three potential effects of EPU due to pandemics on firm operations. First, increasing EPU due to pandemics adversely affects consumer spending. Hassan et al. (2020) suggest that as Covid-19 spread globally in the first quarter of 2020, the increasing uncertainty raises concerns about the collapse of demand and a disruption in supply chains. From this, consumer goods companies which overwhelmingly dependent on the current demand and supply chains would undergo more significant losses in the crisis. As a result, the impact of EPU due to COVID-19 pandemic on volatility could be more pronounced for consumer stocks. Second, a higher level of EPU lowers firms’ investment. Wang et al. (2014) argue that firms with lower returns on invested capital amplify the effect of policy uncertainty. In addition, Gormsen and Koijen (2020) document a decline in investment opportunities due to Covid-19. Firms’ added value decreases significantly in highly uncertain conditions, and therefore sets off investors’ panic. Hence, such investment effects should be more pronounced in less-profitable stocks during pandemics crises. Third, a higher level of EPU caused by pandemic shocks forcing firms to bear higher financing costs (Waisman et al., 2015). Such effects change the expected earnings of firms with relatively higher leverage and lead to higher stock volatility.

![Fig. 1. The theoretical framework of pandemic shocks, EPU, and firm-level volatility.](image-url)
**Hypothesis 2.** The two-dimension effect of COVID-19 pandemic and EPU is most pronounced for consumer, less-profitable, and high leverage stocks.

Finally, we focus on the dynamic effects of pandemics shocks and EPU on stock volatility. Specifically, the EPU could transmit the impact of public health emergency to the economy since the stock market serves as the barometer of investors’ panic sentiment and expectations of economic prospects (Baker et al., 2012). As pandemics continue and then extinguish themselves in a matter of months, the stability of policy expectation will be restored, and the moderation in investors’ panic leads to downward revisions in the additionally increasing volatility (Lee et al., 2002; Zhi et al., 2015). Consequently, stock market volatility responded to the outbreak in a timely manner and gradually recovered as the impact of EPU waned. In fact, to understand how short-term firm-level volatility may be affected in the aftermath of the current pandemics, we could review the impact of SARS. The SARS crisis started in China with a case of atypical pneumonia on 16 November 2002. However, panic had not actually appeared in the stock market until the health minister and the mayor of Beijing were deposed for covering up the high fatality rate in April 2003. As a result, the market index fell 20% in a week. But actually, the difference in trends between stocks with a higher degree of sensitivity to public health policy (such as medicine stocks) and others diminishes when the impact of SARS pandemic ended in June 2006 with the warmer temperature. As shown by Wang et al. (2014) and Donadelli et al. (2017), SARS pandemic should affect the medicine and transportation business through changes in policies like travel restrictions, yet these effects would not be permanent.

**Hypothesis 3.** Third, the two-dimension effects of COVID-19 pandemic and EPU are likely to be persistent in the short term.

### 3. Data

#### 3.1. Daily economic policy uncertainty index

Baker et al. (2016) construct an EPU index for the United States. The measure is a weighted average of three components: the frequency of newspaper references to economic policy uncertainty, the number of federal tax code provisions set to expire, and the extent of forecaster disagreement over future inflation and government purchases. Furthermore, to measure EPU for China, Baker et al. (2016) use the same news-based method to construct a scaled frequency count of articles about policy-related economic uncertainty in the South China Morning Post (SCMP), Hong Kong’s leading English-language newspaper. Nevertheless, the use of SCMP leads to a limitation since it may not fully reflect the level of economic policy uncertainty in mainland China. Therefore, Davis et al. (2019) use two leading mainland Chinese newspapers, Renmin Daily and Guangming Daily, as their news retrieval platform to construct a new China’s EPU, which better reflects the uncertainty of Chinese economic policy.

However, this study mainly concentrated on possible variations of the short-term volatility effects before and after the pandemic outbreak. In this regard, higher frequency EPU indexes are needed to capture a wide range of uncertainty promptly. Hence, we focus on two types of daily EPU index, which are comprehensive EPU and financial EPU. Huang and Luk (2020) develop a daily EPU index\(^4\) of China by counting the number of articles discussing economic policy uncertainty in 10 leading daily Chinese-language newspapers. We use this index as the treatment variable capturing comprehensive EPU information because the text source of which mainly covers general interest news. Given that the existing comprehensive EPU index loses sight of information from financial newspapers, this study constructs a relatively specialized financial EPU index based on 15 leading financial newspapers of mainland China: Economic Daily, China Economic Times, China Enterprise News, China Business Times, Shanghai Securities News, China Business, Financial Times, Securities Times, 21st Century Business Herald, Beijing Business Today, The Economic Observer, Securities Daily, National Business Daily, China Business News, China Securities Journal. The compilation strategy of the daily financial EPU index is similar to that of Huang and Luk (2020). In our research, we are particularly interested in the sensitivity of stock volatility to EPU. Therefore, we use the following time-series regression to estimate the coefficients (\(\beta_{EPU}\)) of comprehensive EPU and financial EPU for each stock based on the rolling windows of the past 22 trading days (approximate number of trading days in one month).

\[
VOL_t = \alpha + \beta_{EPU} EPU_t + \epsilon_t, \tag{9}
\]

where \(VOL_t\) is the conditional volatility for stock at day \(t\), \(EPU_t\) is the daily EPU index at day \(t\), \(\epsilon_t\) is the residual. We repeat Eq. (9) for comprehensive EPU and financial EPU separately and average the series of \(\beta_{EPU}\) estimates to obtain the sensitivity of stock volatility to EPU for each stock in our sample period.

#### 3.2. Conditional volatility measure

The conditional volatility has been received much attention from scholars and then used to measure latent market fluctuations. Therefore in this paper, we employ three widely used conditional volatility models, including the GARCH(1,1) model, the exponentially weighted moving average model, and the rolling window model:

The GARCH model is proposed by Bollerslev (1986) and has been extensively used in measuring conditional variance. The GARCH (1,1) model is our third volatility model, and the conditional variance calculated by the GARCH(1,1) model is:

\[\text{Data sources: https://economicpolicyuncertaintyinchina.weebly.com/}.\]
\[ r_{it} = \mu + \varepsilon_{it}, \]  
\[ \text{and} \]
\[ VOL_{it}^{G} = \omega + \alpha r_{i,t}^2 + \beta VOL_{i,t-1}^{G}. \]

where \( r_{it} \) is the daily return for stock \( i \) at day \( t \); \( \mu, \omega, \alpha, \beta \) are parameters estimated by GARCH(1,1) model; \( \varepsilon_{it} \) is the residual.

Following Dimson and Marsh (1990), an exponential smoothing model is used to forecast volatility. The exponentially weighted moving average model is essentially an exponential smoothing model for the moving average rather than the realized volatility value. In this model, the forecast of volatility is posited to be a function of the immediate past forecast and the immediate past observed volatility. The conditional variance calculated by the exponentially weighted moving average model is:

\[ VOL_{it}^{EW} = \lambda VOL_{i,t-1}^{G} + (1 - \lambda)r_{i,t-1}^2, \]

where \( \lambda \) is the decay factor estimated by minimizing the error of estimate value for variance (herein, \( \lambda = 0.94 \)).

The rolling window model is a natural method to estimate the realized value of volatility. In this paper, we calculate the realized variance of excess returns from a month earlier till the current day via the rolling window model. Then we use this realized variance as a proxy of the conditional variance for the next day’s excess return:

\[ VOL_{it}^{RW} = \frac{1}{N} \sum_{d=0}^{N-1} (r_{i,d} - \mu)^2, \]

where \( N \) is the approximate number of trading days in one month (herein, \( N = 22 \)).

3.3. Sample selection

To thoroughly examine the two-dimension variations of stock volatility under the impact of EPU and the COVID-19 pandemic lockdown impact on 23 January 2020, we restrict the pre- and post-event windows to 2 months (about 40 trading days). Therefore, we select the closing price spanning from 25 November 2019 to 23 March 2020 as the sample period. Our basic sample consists of 300 common stocks in the CSI300 index component, and the panel sample size is around 24,000 observations. To obtain more robust results, we choose three known determinants of stock volatility as control variables, including the book-to-market ratio, turnover rate, and investor sentiment. Here, we choose a technical factor, namely the psychological line, as a daily investor sentiment proxy. These data are obtained from the RESSET® database.

Table 1 reports the summary statistics of the main variables. Specifically, the entire sample is separated into two sub-samples based on the COVID-19 pandemic lockdown on 23 January 2020. By comparing the descriptive statistics summarized in Panel A and Panel B, we can observe concrete evidence that the stock volatility tends to increase and become more correlated with EPU after the COVID-19 pandemic lockdown.

4. Empirical results

4.1. The two-dimension variations of stock volatility

To examine the two-dimension variations of stock volatility under the impact of COVID-19 pandemic and EPU, we conduct a DID estimation and incorporate EPU beta to distinguish the sensitivity of individual stock to EPU. DID estimation enables us to identify causality by comparing the stock volatility changes before and after the COVID-19 pandemic lockdown between stocks with different degrees of sensitivity to EPU. In particular, we consider two different measures of EPU: comprehensive EPU (denoted as \( CEPU \)) and financial EPU (denoted as \( FEPU \)). We specify the following panel regression models:

\[ VOL_{it}^{G} = \alpha_i + \beta_1 D_t + \beta_2 \text{Treat}_{i} \times D_t + \varepsilon_{it}, \]  
\[ \text{and} \]
\[ VOL_{it}^{G} = \alpha_i + \beta_1 D_t + \beta_2 \text{Treat}_{i} \times D_t + \delta_i L \cdot VOL_{i,t-1}^{G} + \delta_2 X_{i,t-1} + \varepsilon_{it}, \]

where \( VOL_{it}^{G} \) is the daily volatility of stock \( i \) at time \( t \). The daily volatility is estimated by the GARCH(1,1) model. \( D_t \) is a time dummy corresponding to the period after the COVID-19 pandemic lockdown. \( D_t \) takes the value 1 during the period from 23 January 2020 to 23 March 2020. \( \text{Treat}_{i} \) is the treatment variable that includes the two types of EPU: measured by comprehensive newspapers news (\( CEPU \)) and financial newspapers news (\( FEPU \)). \( \text{Treat}_{i} \times D_t \) is not separately included in the specification since we add stock fixed effects \( (a) \) to remove all time-invariant differences across stocks. \( \text{Treat}_{i} \times D_t \) is an interaction term between a stock’s treatment status and time.

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5 RESSET Financial Research Database (RESSSET) is mainly for colleges and universities, financial research institutions, research departments of financial enterprises in China, providing support for empirical research and model test. RESSET is designed by numerous experts from Tsinghua University, Peking University, and the London School of Economics.
dummy. $L \cdot VOLG_{i,t}$ is the lagged dependent variable, including the volatility of stock $i$ at time $t-1$ and time $t-2$ to control for persistence. Vector $X_{i,t-1}$ includes a series of known determinants of stock volatility as control variables, including the book-to-market ratio ($BTM$), turnover rate ($Turnover$), and investor sentiment ($Sentiment$). We lag all control variables for one period in order to alleviate endogenous concerns.

In Eqs. (14), (15), we are particularly interested in the estimate of the interaction term ($\beta_2$), which captures the effect of EPU on stock volatility under the impact of COVID-19. For concreteness, the estimated coefficient $\beta_2$ measures the additional increase (or

|                | $CEPU_t$ | $FEPU_t$ | $VOLG_{i,t}$ | $VOLEW_{i,t}$ | $VOLRW_{i,t}$ |
|----------------|----------|----------|-------------|---------------|---------------|
| Mean           | 123.3639 | 71.32567 | 0.0224      | 0.0004        | 0.0175        |
| S.D.           | 66.7925  | 42.94744 | 0.0012      | 0.0000        | 0.0011        |
| Skew.          | 1.8035   | 0.3746   | 0.5699      | 0.8059        | 0.6597        |
| Kurt.          | 7.6390   | 2.8825   | 3.0723      | 4.8241        | 2.8520        |
| Correlation with $CEPU_t$ | 0.5677 | 0.5677 | 0.4012 | 0.0822 | 0.2441 |
| Correlation with $FEPU_t$ | 0.5677 | 0.3519 | 0.0572 | 0.1886 |

|                | $CEPU_t$ | $FEPU_t$ | $VOLG_{i,t}$ | $VOLEW_{i,t}$ | $VOLRW_{i,t}$ |
|----------------|----------|----------|-------------|---------------|---------------|
| Mean           | 134.8299 | 72.7107  | 0.0294      | 0.0009        | 0.0306        |
| S.D.           | 64.5114  | 49.0913  | 0.0041      | 0.0001        | 0.0021        |
| Skew.          | 0.7846   | 0.5633   | 3.4016      | 1.8131        | 2.3855        |
| Kurt.          | 2.9494   | 2.8453   | 16.9740     | 1.8131        | 2.3855        |
| Correlation with $CEPU_t$ | 0.4412 | 0.4412 | 0.2317 | 0.1435 | 0.3077 |
| Correlation with $FEPU_t$ | 0.4412 | 0.4730 | 0.1864 | 0.2615 |

Note: This table reports descriptive statistics of the variables in the two sub-samples. Panel A is for the period ranges from 25 November 2019 to 23 January 2020, covering the 2 months before the COVID-19 pandemic lockdown. Panel B is for the period ranges from 3 February 2020 to 23 March 2020, covering the 2 months after the COVID-19 pandemic lockdown.

### Fig. 2. COVID-19 pandemic lockdown and surge in stock volatility.

Note: This figure shows how the average volatility in two groups of stocks changes during the period of November 2019 to March 2020. Stocks are classified into the low or high EPU-sensitive group based on the median of regression coefficients. Specifically, two types of EPU index are used, including the financial EPU index and the comprehensive EPU index. The vertical reference line at 23 January 2020 indicates the timing of the COVID-19 pandemic lockdown.
decrease) in the volatility of stocks with a higher degree of sensitivity to EPU (relative to those with a lower degree of sensitivity to EPU) after the announcement of the COVID-19 pandemic lockdown at 23 January 2020.

To ensure the validity of DID estimations, we first examine the parallel trend assumption based on the following descriptive analysis.

Fig. 2 illustrates the dynamic trend for the average volatility in two groups of stocks changes during the sample period from November 2019 to March 2020. Stocks are classified into the low or high EPU-sensitive group based on the median of the regression coefficients \( \hat{\beta}_{EPU} \) estimated in Eq. (9). Before the announcement of the COVID-19 pandemic lockdown on 23 January 2020, there are relatively similar trends in the volatility of both groups of stocks, which satisfies the parallel trend assumption. Such a pattern suggests that if there were no COVID-19 pandemic lockdown, the volatility of low and high EPU-sensitive groups would continue to follow a parallel trend in subsequent periods. However, with the announcement of COVID-19 pandemic lockdown, the volatility increases more in stocks with a higher degree of sensitivity to EPU than those with a lower degree of sensitivity to EPU, and the gap between the two groups of stocks also extends over time. This finding implies that stocks with a higher degree of sensitivity to EPU are impacted more by the COVID-19 pandemic lockdown.

Next, we divide the sample period into two sub-periods ranging from November 2019 to 23 January 2020 (before the COVID-19 pandemic lockdown) and from 23 January 2020 to 23 March 2020 (after the COVID-19 pandemic lockdown) and perform univariate tests for the difference of stock volatility between the two sub-periods in high EPU-sensitive and low EPU-sensitive stocks. As shown in Table 2, for high comprehensive EPU-sensitive stocks of which the regression coefficients are larger than the median, the volatility difference between the two sub-periods is 0.91%, which is statistically different from zero at the 1% significance level. Results for low EPU-sensitive stocks also show a significant difference in volatility. More importantly, although the volatility has increased significantly in both stock groups since 23 January 2020, stocks with a higher degree of sensitivity to EPU witness a greater volatility rise than low EPU-sensitive stocks (with a positive difference of 0.35%). These findings hold when we use financial EPU as the treatment variable.

Further, we estimate the DID estimation of Eqs. (14), (15) to confirm whether there is a significant additional increase in the volatility of stocks with a higher degree of sensitivity to EPU after the announcement of the COVID-19 pandemic lockdown on 23 January 2020.

Table 3 represents the panel regression results of the DID estimation. In the first specification, we regress the daily stock volatility over the interaction terms of comprehensive EPU and day dummies. We find that the coefficient estimate for the interaction term (\( \hat{\beta}_2 \)) is positive and statistically significant (coefficient estimate = 0.0143, t statistic = 12.97), suggesting that stocks with a higher degree of sensitivity to comprehensive EPU tend to have higher volatility increase after the COVID-19 pandemic lockdown than in previous trading days. In the second specification, we control for our lagged dependent variables and find this effect to persist. Next, we control for several other known determinants of stock volatility including book-to-market ratio (\( BTM_{i,t-1} \)), turnover rate (\( Turnover_{i,t-1} \)) and investor sentiment (\( Sentiment_{i,t-1} \)). We find in the specification (3) that incorporating all control variables does not affect the nature of the two-dimension variations of stock volatility; our coefficient estimate for the interaction term (\( \hat{\beta}_2 \)) remains negative and significant (coefficient estimate = 0.0051, t statistic = 5.25). In specifications (4), (5), and (6) of Table 3, we document the effect of financial EPU as the treatment variable. We control in (4, 6) for our lagged dependent variables and find this effect to persist. Next, we control for several other known determinants of stock volatility including book-to-market ratio (\( BTM_{i,t-1} \)), turnover rate (\( Turnover_{i,t-1} \)) and investor sentiment (\( Sentiment_{i,t-1} \)). We find in the specification (3) that incorporating all control variables does not affect the nature of the two-dimension variations of stock volatility; our coefficient estimate for the interaction term (\( \hat{\beta}_2 \)) remains negative and significant (coefficient estimate = 0.0051, t statistic = 5.25). In specifications (4), (5), and (6) of Table 3, we document the effect of financial EPU as the treatment variable. We control in (4, 6) for our lagged dependent variables and find this effect to persist.

Overall, the regression results in Table 3 confirm our earlier hypotheses that stocks with a higher degree of sensitivity to EPU tend to have higher volatility increase after the outbreak. We show that controlling for lagged dependent variables and prior known determinants of volatility does not affect our empirical results. Whether comprehensive EPU or financial EPU are used, we reveal that high EPU-sensitive stocks experience a significant increase in volatility relative to low EPU-sensitive stocks.

| Treatment variable | Group                     | Before lockdown | After lockdown | Difference  | t-value |
|--------------------|---------------------------|-----------------|---------------|-------------|---------|
| Comprehensive EPU  | High EPU-sensitive stock  | 0.0216          | 0.0307        | 0.0091***   | 34.16   |
|                    | Low EPU-sensitive stock   | 0.0199          | 0.0254        | 0.0056***   | 17.97   |
|                    | Difference-indifference   |                 |               | 0.0035***   | 34.64   |
| Financial EPU      | High EPU-sensitive stock  | 0.0217          | 0.0330        | 0.0113****  | 25.43   |
|                    | Low EPU-sensitive stock   | 0.0198          | 0.0232        | 0.0034****  | 9.16    |
|                    | Difference-indifference   |                 |               | 0.0079***   | 18.65   |

Note: This table shows the mean comparison test results for the difference of volatility between the two sub-periods in high EPU-sensitive and low EPU-sensitive stocks. Effects of two measures of EPU are evaluated. *** denote 1% significance levels.
4.2. Subsample analyses for firm characteristics

The results from Tables 2, 3 imply the two-dimension effects of COVID-19 pandemic and EPU on stock volatility. To further assess this impact across stock portfolios of different firm characteristics, in this section, we first consider sub-sample analyses of which full

Table 3
Two-dimension variations of stock volatility under the impact of COVID-19 and EPU.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|------------------|-----|-----|-----|-----|-----|-----|
| \( \text{CEPU}_i \times D_t \) | 0.0143*** | 0.0061*** | 0.0051*** | 0.0133*** | 0.0058*** | 0.0044*** |
| (12.97) | (6.26) | (5.25) | (8.78) | (4.36) | (3.38) |
| \( \text{FEPU}_i \times D_t \) | 0.0133*** | 0.0058*** | 0.0044*** | 0.0059*** | 0.0029*** | 0.0037*** |
| (8.78) | (4.36) | (3.38) | (20.52) | (7.24) | (7.35) |
| \( D_t \) | 0.0049*** | 0.0025*** | 0.0033*** | 0.0051*** | 0.0040*** | 0.0037*** |
| (12.97) | (6.26) | (5.25) | (38.25) | (7.02) | (7.02) |
| \( \text{Vol}_{t-1} \) | 0.4817*** | 0.4661*** | 0.4827*** | 0.4827*** | 0.4686*** | 0.4669*** |
| (20.52) | (7.24) | (7.35) | (7.35) | (7.35) | (7.35) |
| \( \text{Vol}_{t-2} \) | 0.0456*** | 0.0320*** | 0.0468*** | 0.0468*** | 0.0330*** | 0.0330*** |
| (4.80) | (7.02) | (7.02) | (7.02) | (7.02) | (7.02) |
| \( \text{BTM}_{t-1} \) | 0.0066*** | 0.0066*** | 0.0066*** | 0.0066*** | 0.0066*** | 0.0066*** |
| (12.97) | (6.26) | (5.25) | (38.25) | (7.02) | (7.02) |
| \( \text{Turnover}_{t-1} \) | 0.0062*** | 0.0062*** | 0.0062*** | 0.0062*** | 0.0062*** | 0.0062*** |
| (20.52) | (7.24) | (7.24) | (7.24) | (7.24) | (7.24) |
| \( \text{Sentiment}_{t-1} \) | 0.0022*** | 0.0022*** | 0.0022*** | 0.0022*** | 0.0022*** | 0.0022*** |
| (7.24) | (7.24) | (7.24) | (7.24) | (7.24) | (7.24) |
| Constant | 0.0220*** | 0.0103*** | 0.0219*** | 0.0219*** | 0.0102*** | 0.0102*** |
| (38.02) | (15.51) | (29.71) | (29.71) | (15.51) | (15.51) |
| Observations | 23,463 | 23,463 | 23,463 | 23,463 | 23,463 | 23,463 |
| R-squared | 0.6265 | 0.7241 | 0.7283 | 0.6250 | 0.7239 | 0.7281 |

Note: This table presents the panel regression results of DID estimations (Eqs. (14) and (15)). The sample is divided into two groups: consumer stocks and non-consumer stocks based on the industry classification of the CSRC (China Securities Regulatory Commission). EPU\(_i\) is the EPU-sensitive level for stock \(i\). \(D_t\) is a dummy variable taking value 1 if day \(t\) is after 23 January 2020 COVID-19 pandemic lockdown and 0 otherwise. The robust t-statistics in parentheses are calculated based on standard errors clustered at the stock. ** and *** denote 5% and 1% significance levels, respectively.

Table 4
Difference-in-differences regressions for industry characteristics.

| Variable | Consumer stocks | Non-consumer stocks |
|------------------|------------------|------------------|
| \( \text{CEPU}_i \times D_t \) | (1) | (2) | (3) | (4) | (5) | (6) |
| \( \text{FEPU}_i \times D_t \) | 0.0217*** | 0.0086*** | 0.0143*** | 0.0055*** | 0.0106*** | 0.0047*** |
| (10.39) | (4.88) | (10.48) | (4.73) | (10.52) | (4.88) | (10.52) |
| \( D_t \) | 0.0025*** | 0.0013*** | 0.0022*** | 0.0022*** | 0.0019*** | 0.0025*** |
| (12.97) | (4.88) | (10.48) | (4.73) | (10.52) | (4.88) | (10.52) |
| \( \text{Vol}_{t-1} \) | 0.5613*** | 0.5635*** | 0.5613*** | 0.5613*** | 0.5613*** | 0.5613*** |
| (20.52) | (7.24) | (20.52) | (7.24) | (20.52) | (7.24) |
| \( \text{Vol}_{t-2} \) | 0.0217 | 0.0243* | 0.0281*** | 0.0281*** | 0.0293*** | 0.0293*** |
| (6.29) | (3.97) | (18.13) | (18.13) | (18.13) | (18.13) |
| \( \text{BTM}_{t-1} \) | -0.0045*** | -0.0045*** | -0.0045*** | -0.0045*** | -0.0045*** | -0.0045*** |
| (3.97) | (18.13) | (3.97) | (18.13) | (3.97) | (18.13) |
| \( \text{Turnover}_{t-1} \) | -0.0001 | -0.0001 | -0.0001 | -0.0001 | -0.0001 | -0.0001 |
| (3.97) | (18.13) | (3.97) | (18.13) | (3.97) | (18.13) |
| \( \text{Sentiment}_{t-1} \) | 0.0028 | 0.0028 | 0.0028 | 0.0028 | 0.0028 | 0.0028 |
| (3.97) | (18.13) | (3.97) | (18.13) | (3.97) | (18.13) |
| Constant | 0.0242*** | 0.0197*** | 0.0250*** | 0.0250*** | 0.0250*** | 0.0250*** |
| (38.02) | (15.51) | (29.71) | (29.71) | (15.51) | (15.51) |
| Observations | 5688 | 5688 | 5688 | 5688 | 5688 | 5688 |
| R-squared | 0.5450 | 0.6983 | 0.5399 | 0.6983 | 0.6411 | 0.6411 |

Note: This table presents the panel regression results of DID estimations (Eqs. (14) and (15)). The sample is divided into two groups: consumer stock and non-consumer stock based on the industry classification of the CSRC (China Securities Regulatory Commission). EPU\(_i\) is the EPU-sensitive level for stock \(i\). \(D_t\) is a dummy variable taking value 1 if day \(t\) is after 23 January 2020 COVID-19 pandemic lockdown and 0 otherwise. The robust t-statistics in parentheses are calculated based on standard errors clustered at the stock. ** and *** denote 5% and 1% significance levels, respectively.

4.2. Subsample analyses for firm characteristics

The results from Tables 2, 3 imply the two-dimension effects of COVID-19 pandemic and EPU on stock volatility. To further assess this impact across stock portfolios of different firm characteristics, in this section, we first consider sub-sample analyses of which full
sample is divided into two groups: consumer stocks and Non-consumer stocks based on the industry classification of the CSRC (China Securities Regulatory Commission).

Table 4 reports the panel regression results of the DID estimation on the consumer stocks relative to non-consumer stocks. In specification (1–2, 5–6), where we use the comprehensive EPU as the treatment variable, we find that all the coefficient estimates for the interaction term \( \beta_2 \) are strongly positive, excluding or including control variables. Interestingly, we also find that the additional average increase in volatility of high EPU-sensitive stocks is higher in the consumer stocks subgroup (0.86%) relative to the non-consumer stocks subgroup (0.55%). At the bottom of Table 4, we present the difference significance between the consumer stocks subgroup and the non-consumer stocks subgroup. The results reveal that the interaction term coefficients for the consumer stocks subgroup are greater than those for the non-consumer stocks subgroup at 1% significance level. Similarly, in (3–4, 7–8), we regress the daily stock volatility over the interaction terms of financial EPU and day dummies. Our findings on the two-dimensional volatility effects of COVID-19 pandemic and EPU on consumer stocks relative to non-consumer stocks remain unchanged.

Moreover, as the pandemic’s effects keep unfolding, the difference in the company’s profitability could have presented several novel features (Bretsch et al., 2020). To explain whether the characteristics of firm profitability affect the two-dimension effects of COVID-19 pandemic and EPU on stock volatility, we group our stocks based on the changes of firms’ earnings per share (EPS) in the first quarter of 2020 and repeat DID regressions (14, 15) for each subsample.

Table 5 presents the results of the DID regressions for profitability characteristics. The estimates with treatment variable of comprehensive EPU, reported in specifications (1)–(2, 5–6), confirm our earlier findings on the positive difference in stock volatility between the high and low EPU-sensitive stocks after the pandemic shock. Specifically, for the regression results of profitable stock shown in specifications (1–2), high comprehensive EPU-sensitive stocks experience an average increase in daily volatility of 0.35% relative to low comprehensive EPU-sensitive stocks. However, such an effect becomes insignificant in specifications (3–4), of which we replace the treatment variable with financial EPU. Comparing the different estimated coefficients between the two subsamples, we reveal that the two-dimension volatility effect is significant and most pronounced for less-profitable stocks. Such differences between the two subsamples are significant at 1% level, as shown at the bottom of Table 5.

Finally, to revisit our finding for high leverage and low leverage stocks, we group our stocks based on the stock’s leverage ratio. Here, the leverage ratio is an equal average of three components: market leverage, book leverage, and asset-liability ratio. Again, we repeat DID regressions (14, 15) for each subsample.

Generally, all coefficient estimates for the interaction term \( \beta_2 \) are significantly positive, excluding or including control variables, confirming the positive difference in stock volatility between the high and low EPU-sensitive stocks after the pandemic shock are economically and statistically significant. Specifically, we reveal that the EPU effect under the impact of COVID-19 is more pronounced for high-leverage stock (with relatively larger \( \beta_2 \)) compared to low-leverage stocks (with relatively smaller \( \beta_2 \)) by comparing results for two sub-samples in the specification (1–4, 5–8), respectively. Furthermore, the differences between the two subsamples are also of statistical significance.

### Table 5

| Variable          | Profitable stocks |                  | Less-profitable stocks |                  |
|-------------------|-------------------|------------------|------------------------|------------------|
|                   | (1)               | (2)              | (3)                    | (4)              |
|                   | (5)               | (6)              | (7)                    | (8)              |
| \( CEPU_i \times D_t \) | 0.0105*** (7.17) | 0.0035** (2.74) | 0.0178*** (10.85)     | 0.0063*** (4.44) |
| \( FEPU_i \times D_t \) | 0.0051*** (20.75) | 0.0031*** (13.71) | 0.0039*** (18.08)     | 0.0048*** (17.39) |
| \( Vol_{t-1} \)   | 0.4537*** (48.32) | 0.4544*** (48.30) | 0.4751*** (50.57)     | 0.4725*** (22.43) |
| \( Vol_{t-2} \)   | 0.0388*** (4.12)  | 0.0396*** (4.21)  | 0.0253*** (2.70)      | 0.0250*** (2.66)  |
| \( BTM_{t-1} \)   | –0.0057*** (10.96) | –0.0058*** (11.08) | –0.0073*** (14.23)    | –0.0072*** (14.10) |
| \( Turnover_{t-1} \) | 0.0022*** (3.40)  | 0.0022*** (3.35)  | 0.0023 (0.65)         | 0.0025 (0.73)    |
| \( Sentiment_{t-1} \) | –0.0027*** (6.66) | –0.0027*** (6.63) | –0.0018*** (3.98)     | –0.0018*** (4.04) |
| \( Constant \)    | 0.0300*** (43.90) | 0.0136*** (18.58) | 0.0136*** (18.61)     | 0.0328*** (41.10) |
| \( Stock FE \)    | Yes               | Yes              | Yes                    | Yes              |
| Observations      | 11,613            | 11,613           | 11,613                 | 11,613           |
| R-squared         | 0.6562            | 0.7463           | 0.6547                 | 0.7462           |
| Difference significance | –5.81*** (5.81) | –5.14*** (5.14) | –3.60*** (3.60)       | –3.60*** (3.60) |
|                  |                   |                  |                        |                  |

Note: This table presents the panel regression results of DID estimations (Eqs. (14) and (15)). The sample is divided into two groups: profitable stocks and less-profitable stocks based on the changes of firms’ EPS in the first quarter of 2020. \( EPU_i \) is the EPU-sensitive level for stock i. \( D_t \) is a dummy variable taking value 1 if day t is after 23 January 2020 COVID-19 pandemic lockdown and 0 otherwise. The robust t-statistics in parentheses are calculated based on standard errors clustered at the stock. The difference significances are determined using the Chow test. The null hypothesis is that the coefficients are equal for the two subsample groups under consideration. ** and *** denote 5% and 1% significance levels, respectively.
4.3. Dynamic effect analyses

In this section, we center on the dynamic effects of Covid-19 lockdown and EPU on stock volatility. By adopting a multi-period DID approach, we provide some insight into the following question. Firstly, the analysis would identify the dynamic marginal evolution of the two-dimension variations of stock volatility under the impact of COVID-19 pandemic and EPU. Secondly, it could reveal potential explanations for whether there are expectation effects or lagging effects through timely updates of estimated coefficients. Finally, for robustness analysis, the parallel trend assumption could be verified. Therefore, to test the dynamic effects, we partition the pre- and post-pandemic periods into 16 trading weeks and obtain DID estimation coefficients on the 16 corresponding interaction terms. In this case, the regression models become:

\[
VOL_{it} = \alpha_i + 0 \sum_{j=1}^{16} Treat_j \times D_{ij} + \delta_1 L \cdot VOLG_{it} + \delta_2 X_{t-1} + \varepsilon_{it},
\]

where \(VOLG_{it}\) is the daily volatility of stock \(i\) at time \(t\). \(D_{ij}\) is a dummy variable for each trading week which equals 1 in week \(j\) and 0 otherwise. \(Treat\) is the treatment variable that includes the two types of EPU: measured by comprehensive newspapers news (CEPU) and financial newspapers news (FEPU). \(Treat\) is not separately included in the specification since we add stock fixed effects (\(\alpha_i\)) to remove all time-invariant differences across stocks. \(Treat \times D_{ij}\) is an interaction term between a stock's treatment status and time dummy. \(L \cdot VOLG_{it}\) is the lagged dependent variable, including the volatility of stock \(i\) at time \(t-1\) and time \(t-2\) to control for persistence. Vector \(X_{t-1}\) includes a series of known determinants of stock volatility as control variables, including the book-to-market ratio (\(BTM\)), turnover rate (\(Turnover\)), and investor sentiment (\(Sentiment\)). We lag all control variables for one period in order to alleviate endogenous concerns. This multi-period DID regression is different from Eq. (16) since we could obtain a total of 16 estimates of the interaction terms from each trading week in our sample period. The daily volatility is estimated by the GARCH(1,1) model.

Fig. 3 depicts the time series of the coefficient estimates for the interaction terms of EPU, including financial EPU and comprehensive EPU, and trading week dummies (\(\theta\)). The regression results for the financial EPU index show that during the two trading weeks following the COVID-19 pandemic lockdown announcement, the high EPU-sensitive stocks become more volatile than the low EPU-sensitive stocks at the 5% level compared with the pre-pandemic period. However, after 10 February 2020, the changes in the two groups of stocks’ volatility are indistinguishable. Chart b of Fig. 3 shows the regression results for the comprehensive EPU index. The

| Variable | High leverage stocks | Low leverage stocks |
|----------|----------------------|---------------------|
| CEPU \(\times D_{i}\) | 0.0176*** (11.11) | 0.0082*** (5.73) |
| FEPU \(\times D_{i}\) | 0.0164*** (6.74) | 0.0085*** (3.86) |
| \(D_{i}\) | 0.0043*** (16.74) | 0.0035*** (14.35) |
| \(Vol_{t-1}\) | 0.3894*** (41.44) | 0.3912*** (41.64) |
| \(Vol_{t-2}\) | 0.0021 (–0.22) | 0.0001 (–0.01) |
| \(BTM_{t-1}\) | 0.0065 (1.25) | 0.0001 (1.19) |
| \(Turnover_{t-1}\) | –0.0042 (–8.76) | –0.0042 (–8.77) |
| \(Sentiment_{t-1}\) | 0.0196*** (25.62) | 0.0025** (2.39) |
| Constant | 0.0198*** (25.79) | 0.0024** (2.29) |
| Stock FE | Yes | Yes |
| Observations | 11,613 | 11,613 |
| R-squared | 0.6909 | 0.6895 |
| Difference significance | (6.56)** | (5.11)** |

Note: This table presents the panel regression results of DID estimations (Eqs. (14) and (15)). The sample is divided into two groups: high leverage stocks and low leverage stocks based on the stock’s leverage ratio. \(EPU\) is the EPU-sensitive level for stock \(i\). \(D_{i}\) is a dummy variable taking value 1 if day \(t\) is after 23 January 2020 COVID-19 pandemic lockdown and 0 otherwise. The robust t-statistics in parentheses are calculated based on standard errors clustered at the stock. The difference significances are determined using the Chow test. The null hypothesis is that the coefficients are equal for the two subsample groups under consideration. *, ** and *** denote 10%, 5%, and 1% significance levels, respectively.
estimates of $\theta_j$s are positive and stable from 17 January 2020 to 24 February 2020, covering five trading weeks. Specifically, there is an expectation effect and a relatively longer duration for the pandemic shock when using the comprehensive EPU index as the EPU proxy. We conclude from such a pattern that the financial EPU index could be more sensitive to pandemic events than the comprehensive EPU index. Overall, the regression results in Fig. 3 confirm our earlier findings on the importance of EPU as a transmission channel through which the COVID-19 pandemic can affect stock volatility. Moreover, it shows that the parallel trend assumption is satisfied, and the pandemic shock takes effect on 23 January 2020 and persists for weeks.

4.4. Robustness analyses

To enhance the reliability of our main conclusions, we conduct several robustness checks. We first consider the following two alternative volatility models in addition to our original measurement of stock volatility, (i) the exponentially weighted moving average model; (ii) the rolling window model.

As shown in Table 7, the estimates of Eqs. (14), (15) with stock volatility calculated by the exponentially weighted moving average model are presented in Panel A, while the estimates with stock volatility calculated by the rolling window model are presented in Panel B. To conclude, the estimates of the interaction term ($\beta_2$) are all positive and statistically significant for all dependent variables, which is consistent with the finding in baseline estimates reported in Tables (3–6) and suggests that our results are robust for using these alternative measures of the key independent variable.

Next, we conduct several placebo tests following Cai et al. (2016) to further address omitted variable bias concerns. Specifically, we generate artificial treatment variables $CEPU_{R_i}$ and $FEPU_{R_i}$ with random assignment of CEPU beta and FEPU beta to stocks under 1000
Table 7
Robustness tests for alternative measures of stock volatility.

| Variable | Full sample stocks | Consumer stocks | Less-profitable stocks | High leverage stocks |
|----------|--------------------|-----------------|------------------------|---------------------|
|          | (1)                | (2)             | (3)                    | (4)                 |
| β         | 0.0155***          | 0.0216**        | 0.0239***              | 0.0175***           |
|          | (3.17)             | (2.02)          | (6.91)                 | (7.10)              |

Panel A: Alternative measures of stock volatility calculated by the exponentially weighted moving average model:

| FEPU_1 × D_t | 0.0024** | 0.0142*** | 0.0195*** | 0.0051** |
|--------------|----------|-----------|-----------|----------|
|              | (2.59)   | (3.03)    | (3.80)    | (2.26)   |

| FEPU_1 × D_t | 0.0059*** | 0.0116*** | 0.0251*** | 0.0043*** |
|--------------|-----------|-----------|-----------|-----------|
|              | (3.10)    | (3.00)    | (3.85)    | (5.16)    |

Panel B: Alternative measures of stock volatility calculated by the rolling window model:

| FEPU_1 × D_t | 0.0133*** | 0.0226*** | 0.0652*** | 0.0362*** | 0.0201*** | 0.0176*** | 0.0564*** |
|--------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|              | (116.88)  | (87.03)   | (95.11)   | (51.24)   | (75.52)   | (50.90)   | (17.09)   |

| FEPU_1 × D_t | 0.0055*** | 0.0065*** | 0.0053*** | 0.0020*** | 0.0093*** | 0.0103*** | 0.0008*** |
|--------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|              | (26.59)   | (50.41)   | (18.78)   | (2.91)    | (5.13)    | (4.37)    | (3.99)    |

| Controls     | Yes       | Yes       | Yes       | Yes       | Yes       | Yes       | Yes       |
|              | (7.12)    | (7.12)    | (7.12)    | (7.12)    | (7.12)    | (7.12)    | (7.12)    |

| R-squared    | 0.7587    | 0.7566    | 0.6907    | 0.7534    | 0.7121    | 0.7139    | 0.6833    |
|--------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|

| R-squared    | 0.7808    | 0.7651    | 0.7782    | 0.7597    | 0.7101    | 0.7157    | 0.6810    |
|--------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|

Note: This table presents the robustness tests for alternative measures of stock volatility. Specifically, columns (1, 3, 5) report the regression of the indicated independent variable on the conditional variance calculated by the exponentially weighted moving average model; columns (2, 4, 6) report the regression of the indicated independent variable on the conditional variance calculated by the moving average model. The sample is divided into two groups: consumer stock and Non-consumer stock based on the industry classification of the CSRC (China Securities Regulatory Commission). EPU is the EPU-sensitive level for stock i. D_t is a dummy variable taking value 1 if day t is after 23 January 2020 COVID-19 pandemic lockdown and 0 otherwise. The robust t-statistics in parentheses are calculated based on standard errors clustered at the stock. * and *** denote 5% and 1% significance levels, respectively.

Simulations of non-repetition sampling.

Placebo test results with random assignment of CEPU beta and FEPU beta to stocks are presented in Table 8. The estimates of the interaction term (β_2) are very close to 0 in all regressions. Consequently, the placebo tests confirm that there is no omitted variable bias in our earlier estimation results.

5. Conclusions

This paper addresses an essential issue of how pandemic shocks like the destructive COVID-19 outbreak can amplify firm-level volatility through EPU channels. Using a DID estimation, we document new empirical facts about the two-dimension variations of stock volatility under the impact of COVID-19 pandemic and two types of EPU: measured by comprehensive newspapers news and financial newspapers news. Notably, we have three main findings. First, we find a significant additional increase in the volatility of stocks with a higher degree of sensitivity to EPU after the announcement of the COVID-19 pandemic lockdown. Second, subsample analyses on firm characteristics confirm that the two-dimension effect of COVID-19 pandemic and EPU is most pronounced for consumer, less-profitable, and high leverage stocks. Third, the dynamic marginal evolution of the two-dimension variations of stock volatility is discontinuous in the whole sampling interval but is stable during the short period after the pandemic outbreak. In addition, our empirical results are still valid after adopting alternative measures of volatility or replacing the treatment variable by randomly assigning EPU to stocks.

Finally, we should point out that the ongoing COVID-19 pandemic is causing havoc around the world. Government restrictions or stimulus will continue to enhance the EPU level. Given these issues, we look back to how the Chinese stock market responded to the travel lockdown in Wuhan, where the COVID-19 pandemic initially outbreak. As we have witnessed with COVID-19, EPU channels matter greatly since the stock prices of some specific firms have experienced great volatility. Our findings provide significant implications for policymakers, regulators, and investors in countries or regions that are currently severely affected by the COVID-19 pandemic. For policymakers, government officials, and the central bank would be required to tackle this challenge. On the one hand, through rolling over current loans, reducing taxes, stimulating household consumption, authorities should improve the capital structure for consumer businesses in badly impaired economic sectors such as retail, travel, and tourism. On the other hand, managing the COVID-19 crisis needs a rational approach such that economic policy issued by authorities requires more forward planning to avoid triggering uncertainty. For regulators, special attention should be paid to monitoring EPU levels in the context of pandemic spread.
Table 8
Placebo test results with random assignment of EPU to stocks.

| Variable          | (1)            | (2)            | (3)            | (4)            | (5)            | (6)            |
|-------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| \( CEPU_iR_t \times D_t \) | -0.0003        | 0.0000         | -0.0001        | 0.0000         | 0.0000         | 0.0002         |
| \( FEPU_iR_t \times D_t \)   | (0.25)         | (0.03)         | (0.16)         | (0.01)         | (0.01)         | (0.19)         |
| \( D_t \)          | 0.0071***      | 0.0012***      | 0.0031***      | 0.0080***      | 0.0026***      | 0.0040***      |
|                   | (30.90)        | (8.70)         | (17.66)        | (30.62)        | (20.51)        | (28.55)        |
| \( Vol_{i,t} \)    | 0.6328***      | 0.6632***      | 0.4123***      | 0.4931***      |                |                |
|                   | (98.49)        | (81.98)        | (70.54)        | (79.72)        |                |                |
| \( Vol_{i,t-1} \)  | 0.2021***      | 0.1401***      | 0.0439***      | 0.0503***      | 0.0040***      | 0.0073***      |
|                   | (31.62)        | (14.77)        | (7.88)         | (5.94)         | (5.94)         | (7.71)         |
| \( BTM_{i,t-1} \)  | -0.0066***     | -0.0066***     |                |                |                |                |
|                   | (-18.10)       | (-16.12)       |                |                |                |                |
| \( Turnover_{i,t-1} \) | 0.0062**      | 0.0062**       | 0.0018        | 0.0022**       | 0.0022**       | 0.0022**       |
|                   | (2.23)         | (2.03)         | (2.03)         | (2.03)         | (2.03)         | (2.03)         |
| \( Sentiment_{i,t-1} \) | -0.0022***    | 0.0022***      | 0.0022***      | 0.0022***      | 0.0022***      | 0.0022***      |
|                   | (-7.28)        | (-7.32)        | (-7.32)        | (-7.32)        | (-7.32)        | (-7.32)        |
| Constant          | 0.0223***      | 0.0103***      | 0.0208***      | 0.0217***      | 0.0217***      | 0.0217***      |
|                   | (248.87)       | (15.51)        | (221.96)       | (19.33)        | (19.33)        | (19.33)        |
| Stock FE          | Yes            | Yes            | Yes            | Yes            | Yes            | Yes            |
| Observations      | 23,463         | 23,463         | 23,463         | 23,463         | 23,463         | 23,463         |

Note: This table presents the average of 1000 estimates by randomly assigning EPU to stocks. The sample is divided into two groups: consumer stock and Non-consumer stock based on the industry classification of the CSRC (China Securities Regulatory Commission). EPU is the EPU-sensitive level for stock i. \( D_t \) is a dummy variable taking value 1 if day t is after 23 January 2020 COVID-19 pandemic lockdown and 0 otherwise. The robust t-statistics in parentheses are calculated based on standard errors clustered at the stock. * and *** denote 5% and 1% significance levels, respectively.

Regulators should take some appropriate measures such as trading restrictions to prevent speculation in EPU sensitive stocks. For investors in financial markets, they should fully weigh the two-dimension variations of firm-level volatility due to EPU and pandemic shock and make reasonable investment decisions.

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References

Altig, D., Baker, S., Barrero, J.M., et al., 2020. Economic uncertainty before and during the COVID-19 pandemic. J. Public Econ. 191, 104274.
Ashraf, B.N., 2020. Stockmarkets’ reaction to COVID-19: cases or fatalities? Res. Int. Bus. Financ. 101249.
Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment. J. Financ. Econ. 104, 272–287.
Baker, S., Bloom, N., Davis, S., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.
Baker, S., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market impact of COVID-19. In: NBER Working Paper. No. w26945.
Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econom. 31, 307–327.
Breitfischer, L., Hsu, A., Simsek, P., Tanoni, A., 2020. COVID-19 and the cross-section of equity returns: impact and transmission. Rev. Asset Pricing Stud. 10 (4), 705–741.
Brogaard, J., Detzel, A., 2015. The asset pricing implications of government. Econ. Pol. Manag. Sci. 61 (1), 3–18.
Caballero, R.J., Simsek, A., 2020. Asset Prices and Aggregate Demand in a “Covid-1” Shock: A Model of Endogenous Risk Intolerance and LSAPs. NBER working paper. No. 27044.
Cai, X., Lu, Y., Wu, M., Yu, L., 2016. Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. J. Dev. Econ. 123 (1), 73–85.
Davis, S.J., Liu, D., Shen, X.S., 2019. Economic Policy Uncertainty in China since 1946: The View from Mainland Newspapers (Working paper).
Dimson, E., Marsh, P., 1990. Volatility forecasting without data-snooping. J. Bank. Financ. 14 (2-3), 399–421.
Donadelli, M., Kizys, R., Riedel, M., 2017. Dangerous infectious diseases: bad news for main street, good news for wall street? J. Financ. Mark. 35, 79–103.
Gorman, N.J., Koijen, R.S., 2020. Coronavirus: Impact on Stock Prices and Growth Expectations (Working Paper).
Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2020. Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1. In: Working Paper.
He, P., Sun, Y., Zhang, Y., Li, T., 2020. COVID-19’s impact on stock prices across different sectors—an event study based on the Chinese stock market. Emerg. Mark. Financ. Tr. 56(10), 2198–2212.
Huang, Y., Lu, P., 2020. Measuring economic policy uncertainty in China. China Econ. Rev. 59, 101367.
Huo, X., Qiu, Z., 2020. How does China’s stock market react to the announcement of the COVID-19 pandemic lockdown? Econ. Pol. Stud. 1, 26.
Lee, W.Y., Jiang, C.X., Indro, D.C., 2002. Stock market volatility, excess returns, and the role of investor sentiment. J. Bank. Financ. 26 (12), 2277–2299.
Liu, L., Ma, F., Zhang, X., Zhang, Y., 2020. Economic policy uncertainty and the Chinese stock market volatility: novel evidence. Econ. Model. 87, 24–33.
Liu, L., Zhang, Z., 2015. Economic policy uncertainty and stock market volatility. Financ. Res. Lett. 15, 99–105.
Narayan, P.K., Phan, B., Liu, G., 2020. COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. Financ. Res. Lett. 101732.
Onali, E., 2020. Covid-19 and Stock Market Volatility. SSRN Electronic Journal, No. 3571453.
Pistor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. J. Financ. 67 (4), 1219–1264.
Pistor, L., Veronesi, P., 2013. Political uncertainty and risk premia. J. Financ. Econ. 110, 520–545.
Shen, H., Liu, R., Xiong, H., Hou, F., Tang, X., 2020. Economic policy uncertainty and stock price synchronicity: evidence from China. Pac.-Basin Financ. J. 101485.
Sun, Y., Bao, Q., Lu, Z., 2020. Coronavirus (Covid-19) outbreak, investor sentiment, and medical portfolio: Evidence from China, Hong Kong, Korea, Japan, and U.S. Pac.-Basin Financ. J. 65, 101463.

Waisman, M., Ye, P., Zhu, Y., 2015. The effect of political uncertainty on the cost of corporate debt. J. Financ. Stab. 16, 106–117.

Wang, Y., Chen, C.R., Huang, Y.S., 2014. Economic policy uncertainty and corporate investment: evidence from China. Pac.-Basin Financ. J. 26, 227–243.

Yang, C., Li, J., Yang, J., 2020. Financial economic policy uncertainty and stock market volatility. In: Working Paper.

Yilmazkuday, H., 2020. Covid-19 effects on the S&P 500 index. In: SSRN Electronic Journal. No. 3555433.

Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Financ. Res. Lett. 101528.

Zhi, D., Engelberg, J., Guo, P., 2015. The sum of all FEARS investor sentiment and asset prices. Rev. Financ. Stud. 28 (1), 1–32.