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Pandemic-induced fear and stock market returns: Evidence from China

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\textbf{ABSTRACT}

We construct a pandemic-induced fear (PIF) index to measure fear of the COVID-19 pandemic using Internet search volumes of the Chinese local search engine and empirically investigate the impact of fear of the pandemic on Chinese stock market returns. A reduced-bias estimation approach for multivariate regression is employed to address the issue of small-sample bias. We find that the PIF index has a negative and significant impact on cumulative stock market returns. The impact of PIF is persistent, which can be explained by mispricing from investors’ excessive pessimism. We further reveal that the PIF index directly predicts stock market returns through noise trading. Investors’ Internet search behaviors enhance the fear of the pandemic, and pandemic-induced fear determines future stock market returns, rather than the number of cases and deaths caused by the COVID-19 pandemic.

\section{Introduction}

As of October 2020, the novel coronavirus disease (COVID-19) has infected more than 38 million people and caused 1.08 million deaths around the world. The COVID-19 pandemic has had a considerable impact on the world economy and financial markets. It is fair to say that the COVID-19 pandemic has created a considerably higher level of fear and anxiety than any other previous global health crisis, such as severe acute respiratory syndrome (SARS) and Ebola virus disease (EVD).

A voluminous literature provides evidence on the impact of the COVID-19 pandemic on financial markets after the spread of the coronavirus. First, some studies focus on the relationship between the pandemic and financial market returns (Baker et al., 2020; Salisu & Vo, 2020). For example, Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020) empirically find that the daily growth in the total confirmed cases and total deaths caused by COVID-19 have significant negative effects on stock returns. Salisu, Akanni, and Raheem (2020) construct a COVID-19 global fear index and evaluate its impact on commodity price returns. Second, previous literature investigates the impact of the pandemic on financial market volatility (Corbet, Hou, Hu, Oxley, & Xu, 2020; Lyôocs, Baumôohl, Výrosp, & Molnár, 2020). Cox, Greenwald, and Ludvigson (2020) use a dynamic asset pricing model to show that wild fluctuations in stock prices are driven by shifts in risk aversion during the pandemic. Baig, Butt, Haroon, & Rizvi (2021) indicate that confirmed cases and deaths from the coronavirus are associated with a significant increase in U.S. market illiquidity and volatility. Bai, Wei, Wei, Li, and Zhang (2021) show that the infectious disease pandemic imposes a significant positive impact on long-term stock market volatility. Albulescu (2021) reveals that COVID-19 new case announcements increase the realized volatility of the S&P 500.

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The COVID-19 pandemic results in financial market declines and volatility increases. The impact of COVID-19 and other global pandemics (SARS, H1N1 virus, and EVD) is mainly because the global health crises and events usually produce strong fears and anxieties (Chen, Jang, & Kim, 2007). Generally, fear is one of a set of basic or innate human moods or emotions that is linked to irrationality (Fernandez-Perez, Fuertes, Gonzales-Fernandez, & Mifire, 2020; Goetzmann, Kim, & Wang, 2015). Investors misattribute fear as information when making investment judgments and decisions (Schwarz & Clore, 1983). Fear increases investor pessimism, leading to investors’ overreaction to bad information or news. Such overreactions cause sell propensities and asset price declines, implying asset price undervaluation. In this paper, “pandemic fear” is defined as investors’ apprehension and concerns over the future spread and disastrous consequences of the COVID-19 pandemic. The fear induced by the pandemic is similar to negative sentiment or fear sentiment, as studied by Chen, Liu, and Zhao (2020). However, several related questions have not been answered. What is the role of “pandemic fear” in forecasting stock market returns? What are the economic mechanisms through which pandemic-induced fear affects stock market returns? Are there any differences between fear and traditional sentiment proxies?

Motivated by these considerations, we measure “pandemic fear” by constructing a COVID-19 pandemic-induced fear index (PIF hereafter) using Internet search volumes following Da, Engelberg, and Gao (2015), and empirically evaluate stock market reactions to pandemic information. We also identify the economic mechanism through which pandemic fear affects stock market returns. We further demonstrate the differences between fear and sentiment proxies. Econometrically, the reduced-bias estimation approach proposed by Amihud and Hurvich (2004) is applied to address the issue of small-sample bias.

In particular, we focus on the impact of pandemic-induced fear on the Chinese stock market. The reasons are summarized as follows. First, COVID-19 was initially reported in Wuhan, China. China experienced the spread of COVID-19 and took actions to control the outbreak much earlier than when the World Health Organization (WHO) characterized COVID-19 as a pandemic. Since March 23, 2020, the domestic pandemic has almost ended in China. Determining a full sample period for the Chinese stock market in the empirical analysis is convenient. Second, the Chinese stock market is still an underdeveloped, speculative, and highly volatile market. Approximately more than 80% of investors are retail investors. Retail investors are usually irrational and do not respond quickly to information shocks (Ben-Rephael, Da, & Israelsen, 2017). China creates a perfectly ideal environment to test how the Chinese stock market reacts to extremely negative information and channels through which fear of the pandemic affects stock returns because the two channels assume an environment with irrational investors. Evidence of the Chinese stock market may also be meaningful to other emerging equity markets.

Our empirical results are documented as follows. (1) The PIF index has a significantly negative impact on future cumulative stock market returns, and the impact is persistent. (2) An asymmetric effect that usually exists in traditional sentiment and attention indicators is not found to be significant. (3) The PIF index has a larger impact on the portfolio returns of high-beta stocks, which confirms the theory of the limits of arbitrage from the perspective of pandemic-related fear. (4) The PIF index affects stock market performance through noise trading, rather than liquidity motivated by irrational investors, implying that information underlying the PIF index does not overlap that of traditional sentiment proxies. (5) The fear induced by the pandemic is endogenously triggered by COVID-19 cases and plays a more important role than economic fundamentals or substances in affecting future stock returns. Fear of the COVID-19 pandemic but not the “fundamental” consequence (new cases and deaths) determines stock market performance because Internet search behaviors enhance the fear of the pandemic.

Our work contributes to the growing literature on the measure of fear induced by the global health crisis. Previous studies consider the measure of moods and emotions induced by weather and hazards. For example, Goetzmann et al. (2015) utilize weather-induced mood and investigate the impact on U.S. institutional investors. Fernandez-Perez et al. (2020) evaluate the role of “hazard fear” in commodity futures pricing. However, measures of fear induced by specific events, such as the global health crisis, are quite limited. One exception is Lyocsa et al. (2020), who collect 19 keywords related to the COVID-19 pandemic and construct a fear index using Google search volume. However, they do not specify how the keywords are selected, and some of their keywords are not directly related to the pandemic.

In this paper, we consider a more precise set of pandemic-related keywords collected from local Chinese newspapers, social networks, and government pandemic reports and construct a comprehensive pandemic-induced fear (PIF) index at a daily frequency for China. Following Da et al. (2015), we apply Baidu indices instead of Google search volumes for pandemic-related terms. The PIF index directly and precisely measures the fear led by the COVID-19 pandemic in the Chinese stock market.

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1. Whether fear is rational or irrational is still being discussed. In this paper, we assume that fear is irrational, as stated in many studies (Fernandez-Perez et al., 2020).
2. Some studies and readers may think that sentiment should be orthogonal to macroeconomic conditions and that moods or emotions are not investor sentiment measures because they are driven by fundamental news and events. However, Qiu and Welch (2004) and Da et al. (2015) argue that sentiment should be expected to be endogenous to macroeconomic news and events, which confirms that our pandemic-induced fear, the index of Chen et al. (2020) and Gonzalez-Fernandez and Gonzalez-Velasco (2020) can be seen as event-driven sentiment. We also discuss this issue in Section 5.1.
3. Regional outbreaks occurred in Beijing, Urumqi, and Qingdao after June 2020, and China successfully controlled them.
4. Liquidity is a traditional indicator of investor sentiment (Baker & Stein, 2004; Baker & Wurgler, 2006).
5. Lyocsa et al. (2020) consider 19 keywords related to the pandemic, including “restriction,” “travel,” “MERS,” and “postpone,” which are not directly related to the COVID-19 pandemic. These keywords may be searched for other purposes.
6. (1) Google is not accessible to Chinese investors, and Baidu.com is the largest Internet search engine in China. The Baidu Index is based on the search frequencies and behaviors of the Chinese, which is similar to Google search volume. (2) Lyocsa et al. (2020) and Chen et al. (2020) also use the Internet search volume to capture fears from the pandemic but focus on the impact of the fear index on the U.S. stock market volatility and Bitcoin prices, respectively. 
Our work also contributes to the literature on the interplay between the pandemic, pandemic-induced mood, and asset prices. Using the PIF index, we reveal the impact of the COVID-19 pandemic on cumulative stock market returns from the perspective of moods or emotions. Unlike previous studies that simply quantify the impact of the pandemic (Chen et al., 2007; Ichev & Marine, 2017), we provide several additional tests of whether an asymmetric effect of the PIF index exists on stock market returns by introducing an interaction term of fear and negative returns in the regression and whether the impact can be enhanced by limits of arbitrage through regressing high-beta portfolio returns on the PIF index. We further examine the economic mechanisms through which fear derived from the pandemic affects stock market returns. Two channels related to mispricing are noise trading and liquidity from irrational investors (Baker & Stein, 2004; Goetzmann et al., 2015). In addition, we provide new evidence on how the stock market reacts to extremely negative news or information, which extends the literature on information absorption, as studied by Savor (2012), Engelberg, Sasseville, and Williams (2012), and Frank and Sanati (2018), who consider whether the stock market overreacts or underreacts to bad-information shocks.

Finally, we employ a reduced-bias estimation approach proposed by Amihud and Hurvich (2004) to address the issue of a small-sample bias. Our sample period is from January 20 to August 31, 2020, which corresponds to 149 daily observations. A small-sample bias in Stambaugh (1999) and Amihud and Hurvich (2004) occurs in estimating the impact of the PIF index on stock returns. The small-sample bias may distort the t-statistic when the predictors are Gaussian first-order autoregressive with errors that are correlated with errors of stock returns, implying that we cannot accurately reveal the impact of the PIF index on stock market returns. The small-sample bias is solved using the reduced-bias estimation method for multivariate regressions proposed by Amihud and Hurvich (2004).

The remainder of this paper is organized as follows. Section 2 presents the construction of the PIF index, stock returns, and other control variables. Section 3 describes the reduced-bias estimation approach. Section 4 shows the empirical results. Section 5 describes the robustness checks, and Section 6 concludes.

2. Data

2.1. Construction of the pandemic-induced fear index

To construct the PIF index using the Baidu search volume index (SVI), we first select a list of search terms or keywords related to the COVID-19 pandemic. We select eight keywords that have been frequently mentioned in local Chinese newspapers, on social network platforms, and in government pandemic reports. The keywords include “COVID,” “COVID-19,” “novel coronavirus pneumonia,” “coronavirus pandemic,” “novel pneumonia,” “coronavirus,” “coronavirus pneumonia,” and “pandemic” (see Table 1). We input each keyword into the Baidu Index, which then retrieves the daily search volume index for the corresponding keyword. Our eight keywords finally generate eight search volume indices (SVI). We download the eight indices from the Baidu Index website, and for the search term or keyword i, we take the natural logarithm of its SVI:

$$\Delta SVI_{i,t} = \log(SVI_{i,t}) - \log(SVI_{i,t-1})$$

Following Da et al. (2015), we adjust the eight $\Delta SVI$ series in three steps. First, we winsorize each series at the 2.5% level in each tail. Second, we regress each winsorized series on weekday and month dummies and keep the residual to eliminate seasonality. Third, we standardize each series by dividing the standard deviation after subtracting the average for each series, as in Da et al. (2015). After these adjustments, we obtain the winsorized, deseasonalized, and standardized daily change $\Delta SVI_{i,t}^{adj}$ for the eight keywords. We sum these adjusted series and construct the PIF index as:

$$PIF_t = \sum_{i=1}^{8} \Delta SVI_{i,t}^{adj}.$$  

Why is the PIF index a suitable measure of pandemic-induced fear? The answers to this question are intuitive. Information needs to attract investor attention before it can be processed and incorporated into asset prices by trading (Ben-Rephael et al., 2017). When Chinese retail investors are concerned about the pandemic, they pay attention to pandemic-related information and search for information from Baidu.com, the largest and most popular search engine in China. For example, the SVI for “pandemic” dramatically increased in January 2020. It remained relatively high during February and March 2020, when the pandemic was quite severe in China and the fear induced by the pandemic was high. The SVI directly reflects investors’ fears and concerns about the pandemic, which guarantees that the PFI constructed from the SVI is suitable for measuring fear and anxiety during the COVID-19 pandemic. Interestingly, the PFI index can also serve as a pandemic-driven sentiment indicator, according to González-Fernández and González-Velasco (2020), Lyócsa et al. (2020), and Chen et al. (2020).

2.2. Stock market data and control variables

We calculate the Chinese stock market returns as the natural logarithm of the Shanghai Composite Index daily prices. We include these four control variables: economic policy uncertainty (EPU); realized market volatility (RV); number of cases including newly reported, suspected, and deaths (CASE); and turnover (TURN). Huang and Luk (2020) construct the China economic policy uncertainty

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7 These keywords are summarized in English in Table 1 but are searched for in Chinese.

8 The website of the Baidu Index is index.baidu.com/.
The number of cases is computed as the summation of daily reported, suspected, and death cases, reflecting the pandemic trends uncertainty derived from economic fundamentals (Fang, Su, & Sinko, 2011). The number of cases is computed as the summation of daily reported, suspected, and death cases, reflecting the pandemic trends uncertainty derived from economic fundamentals (Fang, Su, & Sinko, 2011).

The stock market returns and control variables are measured at a daily frequency from January 20 to August 31, 2020. The daily stock market index prices, daily turnover, and 5-min stock market index prices are obtained from the WIND database. The daily China EPU index is available from the website of economic policy uncertainty in China, and we take the natural logarithm of the numbers of cases. The descriptive statistics are reported in Table 1. All variables are stationary, except for CASE, and we consider its first difference.

### 3. Reduced-bias estimation approach for small samples

We use standard predictive regressions to investigate the impact of the PIF index on Chinese stock market returns and employ a reduced-bias estimation approach for multivariate predictive regressions, as in Amihud and Hurvich (2004).

A typical predictive regression with control variables, in which all predictors evolve according to a stationary Gaussian vector autoregressive VAR(1) process, is described as follows:

\[
y_t = \alpha + \beta x_{t-1} + u_t,
\]

\[
x_t = \Theta + \Phi x_{t-1} + v_t,
\]

where \(y_t\) is a scalar dependent variable (returns), \(\alpha\) is a scalar intercept, \(\beta\) is a \(p \times 1\) vector of coefficients, \(\{u_t\}\) is a scalar error term, \(\{x_t\}\) is a \(p \times 1\) vector of predictors, \(\Theta\) is a \(p \times 1\) vector of intercepts, \(\Phi\) is a \(p \times p\) coefficient matrix in which the absolute values of all eigenvalues are less than one to ensure stationarity, and \(\{v_t\}\) is a \(p \times 1\) vector of shocks such that the vectors \(\{u_t, v_t\}'\) are i.i.d. multivariate normal with mean zero. It follows from our assumptions that there exists a \(p \times 1\) vector \(\phi\) such that

\[
u_t = \phi' v_t + e_t,
\]

where \(\{e_t\}\) are i.i.d. normal random variables with mean zero and are independent of both \(\{v_t\}\) and \(\{x_t\}\). Using Eq. (5), we rewrite Eq. (3) as

\[
y_t = \alpha + \beta x_{t-1} + \phi' v_t + e_t.
\]

According to Amihud and Hurvich (2004), the OLS estimator \(\hat{\beta}\) for Eq. (6) is unbiased, implying that \(E(\hat{\beta}) = \beta\). In estimating Eq. (6), the errors \(\{v_t\}\) are unobservable. Amihud and Hurvich (2004) construct a proxy \(\{v_t^*\}\), as follows:

\[
v_t^* = x_t - \bar{\Theta} - \bar{\phi}' x_{t-1},
\]

Notes: This table reports the descriptive statistics and the keywords for the Baidu search volume index. The summary statistics are presented in Panel A. The keywords are reported in English in Panel B, and are searched in Chinese. AR p-value denotes the p-value for the estimated coefficient of autoregression for each variable. ADF p-value denotes the one-sided p-value of the Augmented Dickey-Fuller test for each variable.

Many other traditional proxies for sentiment are considered by Baker and Wurgler (2007). Given the data availability and frequencies, in our paper, we only consider turnover.

The WIND database provides Chinese stock market data at various frequencies, and the website is wind.com.cn/.

https://economicpolicyuncertaintyinchina.weebly.com/
where $\hat{\theta}$ and $\hat{\Phi}$ are any estimators of $\theta$ and $\Phi$ constructed from $(x_t)$, respectively.

An important question is how to obtain $\hat{\Phi}$. If the true $\Phi$ is diagonal, then each entry of $(x_t)$ is a univariate AR(1) process, and the estimation procedure is simple. However, the coefficient matrix $\Phi$ is non-diagonal according to VAR(1) with all of the predictors, and we are more interested in the case of non-diagonal $\Phi$. Amihud and Hurvich (2004) estimate $\Phi$ using the expression from Nicholls and Pope (1988) for the bias in the OLS estimator $\hat{\Phi} = E(\Phi - \hat{\Phi}) = -b/n + O(n^{-3/2})$, where

$$b = \mathrm{tr}\left((I - \Phi')^{-1} + \Phi'(I - \Phi')^{-1} + \sum_{\lambda \in \mathrm{Spec}(\Phi')} \lambda (I - \lambda \Phi')^{-1}\right)\Sigma^{-1},$$

(8)

$I$ is a $p \times p$ identity matrix, $\Sigma_x = \mathrm{Cov}(x_t)$, $\lambda$ denotes an eigenvalue of $\Phi'$, and the notation $\lambda \in \mathrm{Spec}(\Phi')$ indicates that the sum is to be taken over all $p$ eigenvalues of $\Phi'$, with each term repeated as many times as the multiplicity of $\lambda$. Eq. (8) shows that the bias in $\hat{\Phi}$ depends on the unknown $\Phi$ and $\Sigma_x$. Amihud and Hurvich (2004) propose an iterative estimation procedure by repeatedly plugging in preliminary estimates of $\Phi$ and $\Sigma_x$. The bias-corrected estimator $\hat{\Phi}^c$ at each iteration is obtained by subtracting the estimated bias expression from the OLS estimator. The preliminary estimate of $\Sigma_x$ is calculated as the sample covariance matrix of the residuals in Eq. (4), and the preliminary estimate of $\Phi$ is the Yule-Walker estimator. An iterative procedure is used to estimate $\hat{\Phi}^c$ by checking whether the OLS estimator $\hat{\Phi}$ corresponds to a stationary model. If so, it is used as the preliminary estimator and plugged into the bias Eq. (8) with the preliminary estimator of $\Sigma_x$. If the model corresponding to $\hat{\Phi}$ is nonstationary, the Yule-Walker estimator is used and plugged into Eq. (8). These steps yield a first-stage bias-corrected estimator $\hat{\Phi}^c$. If $\hat{\Phi}^c$ corresponds to a nonstationary model, then we set $\hat{\Phi}^c = \hat{\Phi}^c$, and the iteration terminates. Otherwise, we proceed to the next stage of the iteration. The estimator $\Sigma_x$ is also re-estimated at each stage with $\hat{\Phi}^c$.

This estimation approach provides a general framework for multivariate predictive regressions with small samples. We apply this reduced-bias estimation approach in Section 4.

4. Empirical results

4.1. Pandemic-induced fear and stock market returns

To investigate the impact of the PIF index on Chinese stock market returns, we first consider the following econometric specification with control variables (EPU, RV, CASE, and TURN):

### Table 2
Pandemic-induced fear and stock market return forecasting.

| Panel A: Cumulative stock market return forecasting with control variables |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| RET$\_t$ + 1                | RET$\_t$ + 2                | RET$\_t$ + 3                | RET$\_t$ + 4                | RET$\_t$ + 5                | RET$\_t$ + 10               |
| PIF$\_t$                    | -0.021 (0.186)              | -0.591** (0.293)            | -1.285*** (0.363)           | -1.462*** (0.407)           | -1.382*** (0.439)           | -1.631*** (0.584)           |
| EPU$\_t$                    | -0.167 (0.200)              | -0.128 (0.315)              | 0.082 (0.396)               | -0.030 (0.446)              | -0.231 (0.480)              | 0.337 (0.651)               |
| RV$\_t$                     | -23.780 (17.156)            | -9.201 (27.018)             | 17.862 (33.416)             | -3.942 (37.547)             | -1.766 (40.335)             | -10.971 (53.607)            |
| CASE$\_t$                   | 0.208 (0.200)               | 0.382 (0.315)               | 0.348 (0.390)               | 0.545 (0.439)               | 0.920* (0.471)              | 0.937 (0.631)               |
| RET$\_t$                    | -0.098 (0.087)              | -0.079 (0.138)              | 0.019 (0.170)               | -0.144 (0.192)              | -0.066 (0.206)              | -0.192 (0.275)              |
| TURN$\_t$                   | 0.991** (0.481)             | 0.652 (0.757)               | -0.326 (0.937)              | -0.781 (1.051)              | -1.541 (1.128)              | -5.084*** (1.502)           |
| Cons.$\_t$                  | -0.144 (0.360)              | 0.139 (0.568)               | 0.791 (0.704)               | 1.635** (0.791)             | 2.420*** (1.850)            | 5.770*** (1.124)            |
| Adj-$R^2$                   | 23.205%                    | 12.605%                    | 13.010%                    | 13.573%                    | 15.243%                    | 18.834%                    |

| Panel B: Stock market return forecasting with control variables |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| RET$\_t$                    | RET$\_t$ + 1                | RET$\_t$ + 2                | RET$\_t$ + 3                | RET$\_t$ + 4                | RET$\_t$ + 5                |
| PIF$\_t$                    | -0.186 (0.166)              | -0.571*** (0.212)           | -0.692** (0.208)            | -0.174 (0.190)              | 0.096 (0.190)               |
| EPU$\_t$                    | 0.274 (0.197)               | 0.040 (0.228)               | 0.194 (0.227)               | -0.087 (0.208)              | -0.218 (0.208)              |
| RV$\_t$                     | -76.481*** (15.233)         | 14.543 (19.562)             | 26.982 (19.141)             | -23.643 (17.491)            | 2.961 (17.443)              |
| CASE$\_t$                   | -0.236 (0.183)              | 0.174 (0.228)               | -0.030 (0.223)              | 0.169 (0.204)               | 0.373** (0.204)             |
| RET$\_t$                    | -0.017 (0.100)              | 0.099 (0.098)               | -0.177** (0.089)            | 0.083 (0.089)               |
| TURN$\_t$                   | 1.134*** (0.434)            | -0.336 (0.548)              | -0.982* (0.537)             | -0.458 (0.490)              | -0.760 (0.488)              |
| Const.$\_t$                 | -0.103 (0.364)              | 0.279 (0.411)               | 0.665 (0.403)               | 0.873** (0.368)             | 0.766 (0.368)               |
| Adj-$R^2$                   | 18.028%                    | 0.849%                     | 3.415%                     | 3.357%                     | 1.301%                     |

| Panel C: Univariate stock market return forecasting with control variables |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| RET$\_t$                    | RET$\_t$ + 1                | RET$\_t$ + 2                | RET$\_t$ + 3                | RET$\_t$ + 4                | RET$\_t$ + 5                |
| PIF$\_t$                    | -0.187 (0.163)              | -0.409** (0.163)            | -0.316** (0.164)            | -0.494*** (0.162)           | -0.415** (0.162)            | 0.139 (0.157)               |
| Const.$\_t$                 | 0.087 (0.126)               | 0.104 (0.125)               | 0.104 (0.127)               | 0.122 (0.126)               | 0.139 (0.126)               | 0.126 (0.116)               |
| Adj-$R^2$                   | 0.204%                     | 2.989%                     | 4.845%                     | 3.217%                     | -0.526%                    |

Notes: This table reports the impact of the pandemic-induced fear on the stock returns as in Eq. (9). Cons. denotes the constant, and Adj-$R^2$ denotes the adjusted-$R^2$. The Amihud and Hurvich (2004) reduce-bias estimation method is utilized. The numbers in parentheses are standard errors. ***, ** and * denote 1%, 5% and 10% significant level, respectively.
where $RET_{t+1:t+k}$ is the cumulative return from day $t+1$ to $t+k$ ($k \neq 1$). If $k = 1$, Eq. (9) becomes a traditional predictive regression. The Amihud and Hurvich (2004) reduced-bias estimator is used in estimating Eq. (9).

The estimation results are reported in Panel A of Table 2. We find that PIF has a significant and negative impact on the $k$-day cumulative returns for $k = 2, 3, 4, 5, 10$. For example, the estimated coefficient of PIF is $-1.285$ at the 1% significance level when $k = 3$. The impact of PIF on the return of the next day is negative but not significant. The negative signs of the estimated coefficients of PIF indicate that the fear induced by the COVID-19 pandemic leads to lower stock market returns. Our results also suggest that fear of the pandemic is persistent in the stock market for 10 days. Moreover, the contemporaneous relationships between PIF and stock market returns are insignificant. Pandemic-induced fear matters only for the returns of future trading days.

Panel B reports the predictive ability of PIF on the stock return of a single day for longer horizons, and Panel C presents the univariate regression results using PIF as the explanatory variable. PIF significantly and negatively predicts the stock returns of the next 2 and 3 days after controlling for economic policy uncertainty, realized volatility, number of cases, and turnovers. Because turnover is a measure of sentiment related to stock market fundamentals, the PIF index contains different information from traditional proxies for sentiment. For longer horizons, increases in PIF predict higher returns, implying a reversal in the prediction. However, this reversal seems to be insignificant at all levels. As documented by Baker and Wurgler (2006) and Goetzmann et al. (2015), a reversal can be explained by mood-induced mispricing. Pandemic-induced fear leads to stock price undervaluation, which reflects investors’ overreaction to extremely negative information about the pandemic. Because the insignificant reversal occurs after 5 trading days, the undervaluation resulting from the pandemic-induced fear is persistent.

In addition, we find that the estimated coefficients for EPU are not significant at any level. Our results actually indicate that fear induced by the COVID-19 pandemic plays a more important role than economic fundamentals in affecting stock returns, thereby confirming the conclusion of Cox et al. (2020) that the stock market is more reflective of sentiment than substance.

If we consider the PIF index as a negative sentiment measure following Chen et al. (2020) and González-Fernández and González-Velasco (2020), we find that several differences exist between PIF and traditional proxies of sentiment. First, Da et al. (2015) document that the prediction of investor sentiment is temporary reversal. Our results show that the undervaluation caused by the fear of the pandemic may not have a significant contemporaneous impact on $RET_{t+1}$. Because the commission report for day $t$ is on the same day for stock market return $RET_{t+1}$, an increase in $PIF_{t+1}$ may not have a significant contemporaneous impact on $RET_{t+1}$. Second, a significant contemporaneous relationship usually exists between sentiment and stock returns. We find that the fear induced by the pandemic does not lower same-day returns. The reason for these differences may be described as follows. (1) The PIF is driven by the government’s daily released number of COVID-19 cases (which we will confirm in Section 5.1). Investors receive news about COVID-19 cases and then search for more details, leading to concerns and panics about the pandemic. In China, the number of COVID-19 cases for day $t$ is released by the National Health Commission of the People’s Republic of China on day $t + 1$. Investors on day $t + 1$ receive the released news of COVID-19 cases for day $t$ and search for more details about the pandemic, leading to an increase in $PIF_{t+1}$. Because the commission report for day $t$ is on the same day for stock market return $RET_{t+1}$, an increase in $PIF_{t+1}$ may not have a significant contemporaneous impact on $RET_{t+1}$. (2) Most Chinese investors are retail investors who are not professional regarding making investment decisions. Individual investors do not immediately sell stocks when they feel
strong fear but sell stocks following other investors, which reflects the herd phenomenon (Chang, McAleer, & Wang, 2020; Hsieh, Chan, & Wang, 2020; Hudson, Yan, & Zhang, 2020).

4.2. Asymmetric effect of pandemic-induced fear

Fear has a considerable impact on future stock market returns. In this subsection, we continue to examine whether the impact of PIF is different under different stock market conditions. For example, a bad market condition may enhance investors’ fear and strengthen the effect of fear on future stock market returns. In contrast, a good market condition may partially offset the fear induced by the pandemic. To examine whether the asymmetric effect of pandemic-induced fear exists, we consider the following model:

$$\text{RET}_{t+1:k} = \beta_0 + \beta_1 \text{PIF}_t + \beta_2 \text{PIF}_t \cdot D_t + \sum_m \gamma_m \text{control}_m + \epsilon_{t+1:k}.$$  \hspace{1cm} (10)

where $D_t = 1$ if $\text{RET}_t < 0$, and $D_t = 0$ otherwise. During a bad market condition, the impact of PIF on future stock returns will be $\beta_1 + \beta_2$. During a good condition, the impact will be $\beta_1$. The sign and significance of the estimated $\beta_2$ show whether the impact of pandemic-induced fear is asymmetric. The coefficients are estimated using the reduced-bias estimation approach of Amihud and Hurvich (2004).

The estimation results for Eq. (10) are reported in Table 3. The impact of the PIF index on cumulative stock returns is still significant and negative when $k = 2, 3, 4, 5, 10$ after including the interaction term $\text{PIF}_t \cdot D_t$. We are more interested in the asymmetric effects of the PIF index. In Panel A, the coefficients of the interaction term are insignificant, except for the regression when $k = 2$ (1.008 at the 10% significance level). Moreover, the estimated coefficients are almost positive, and past bad market performance weakens the negative impact of the PIF on future stock returns. In Panel B, we find that the coefficient of the interaction term is negative and significant when we use the PIF index to predict the 3rd-day return in the future, showing that an asymmetric effect exists only for a longer horizon.

The overall results demonstrate that the asymmetric effects of “pandemic fear” may not be significant in the Chinese stock market. Why are the asymmetric effects almost insignificant for the impact of fear induced by the COVID-19 pandemic? The answer to this question can be found in the previous psychology literature. The pandemic is the most devastating event to occur in 2020—nothing else, including bad stock market conditions, is worse than the pandemic. During the COVID-19 pandemic, investors could not be more pessimistic, and they became much less sensitive to other bad information, resulting in the disappearance of asymmetric effects.

4.3. Pandemic-induced fear and limits to arbitrage

Pandemic-induced fear can also be considered pandemic-induced sentiment or fear sentiment (Chen et al., 2020). Previous studies argue that one of the most important channels that exacerbates the effect of fear or sentiment on asset prices is limits to arbitrage (Baker & Wurgler, 2006; Baker & Wurgler, 2007; Shleifer & Vishny, 1997). According to the limits of the arbitrage channel, high-beta stocks reflect the speculations of sentiment investors and are less attractive to arbitrageurs who face institutional constraints (Baker, Bradley, & Wurgler, 2011; Da et al., 2015). Therefore, fear or negative sentiment should have a larger impact on the returns of high-beta stocks than those of low-beta stocks. In this subsection, we continue to examine the effect of pandemic-induced fear by regressing beta-sorted portfolio returns on the PIF index and control variables, following Da et al. (2015).

To obtain the beta-sorted portfolios, we first collect the daily returns of all stocks on the Shanghai Stock Exchange from the WIND database and regress the return series of each stock on the market returns of the Shanghai Composite Index. Next, we sort the stocks into three groups (high, medium, and low) using the breakpoints of the 30th and 70th beta percentiles. Finally, we calculate the high-beta stocks than those of low-beta stocks. In this subsection, we continue to examine the effect of pandemic-induced fear by regressing beta-sorted portfolio returns on the PIF index and control variables, following Da et al. (2015).

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$$\text{RET}_{t+1:k}^{\text{high or low}} = \beta_0 + \beta_1 \text{PIF}_t + \sum_m \gamma_m \text{control}_m + \epsilon_{t+1:k}.$$  \hspace{1cm} (11)

The estimation results are presented in Table 4. Panels A and B report the impact of the PIF index on the equally weighted high-beta and low-beta portfolio returns, respectively. Panels C and D report the impact of PIF on the value-weighted high-beta and low-beta portfolio returns, respectively.

As displayed in Panels A and B (Panels C and D), we find that the absolute estimates of PIF for high-beta portfolio returns are larger than those for low-beta portfolio returns, indicating that pandemic-induced fear has a larger impact on high-beta stock portfolio returns. For example, the estimated coefficient of PIF for the high-beta portfolio is $-1.677$ at the 1% significance level when $k = 3$, which is larger than that for the low-beta portfolio ($-0.831$ at the 1% significance level). Our results confirm that limits to arbitrage enhance the impact of PIF. Moreover, the pandemic has a negative impact on the whole stock market. The fear induced by the pandemic naturally has a larger impact on the returns of high-beta stocks considering the essence of market beta.

We also observe that the PIF has a more significant impact on the equally weighted portfolio returns than the value-weighted portfolio returns in Table 4. For example, the coefficient estimates for PIF are all significant when $k = 3, 4, 5, 10$, as reported in Panels A and B, while most of the estimates for PIF are insignificant, as shown in Tables C and D. Previous studies indicate that stocks with smaller sizes have higher betas. Therefore, PIF has a larger impact on small-size stocks, and the significant impact of PIF on the equally weighted portfolio returns is actually driven by the impact of PIF on the returns of small-size stocks.
induced fear on realized volatility. We employ the linear volatility predictive regression in Eq. (12) following Paye (2012): traders make trading decisions according to sentiment or mood, changes in sentiment or mood lead to more noise trading, greater

denotes the adjusted-

Table 5
Pandemic-induced fear and stock market volatility.

| PIF | RET$_{t+1}i$ | RET$_{t-1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ |
|-----|-------------|-------------|-------------|-------------|-------------|-------------|
|    | 0.054 (0.307) | -0.755 (0.473) | -1.677*** (0.593) | -1.999*** (0.662) | -1.907*** (0.695) | -1.978** (0.901) |
| Control | YES | YES | YES | YES | YES | YES |
| Adj-R$^2$ | 14.670% | 9.998% | 8.545% | 8.908% | 12.037% | 14.736% |

Panel C: Pandemic-induced fear and equal-weighted high-beta portfolio

| PIF | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ |
|-----|-------------|-------------|-------------|-------------|-------------|-------------|
|    | 0.024 (0.174) | -0.229 (0.262) | -0.389* (0.329) | -0.664* (0.394) | -0.338 (0.450) | -0.895 (0.673) |
| Control | YES | YES | YES | YES | YES | YES |
| Adj-R$^2$ | 16.594% | 7.680% | 8.500% | 7.570% | 6.127% | -2.244% |

Panel D: Pandemic-induced fear and value-weighted high-beta portfolio

| PIF | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ | RET$_{t+1}i$ |
|-----|-------------|-------------|-------------|-------------|-------------|-------------|
|    | 0.003 (0.072) | -0.051 (0.103) | -0.087 (0.132) | -0.124 (0.157) | 0.036 (0.184) | -0.232 (0.299) |
| Control | YES | YES | YES | YES | YES | YES |
| Adj-R$^2$ | 16.672% | 27.365% | 33.666% | 37.824% | 38.172% | 37.177% |

Notes: This table reports the impact of the pandemic-induced fear on the high-beta (low-beta) portfolio returns as in Eq. (11). Cons. denotes the constant, and Adj-R$^2$ denotes the adjusted-R$^2$. The Amihud and Hurvich (2004) reduce-bias estimation method is utilized. The numbers in parentheses are standard errors. *** and * denote 1%, 5% and 10% significant level, respectively.

4.4. Noise trading or liquidity?

Why does pandemic-induced fear significantly affect stock market returns? Previous studies usually consider two economic channels. The first channel is noise trading led by sentiment or mood, which usually results in higher volatility. When uniform noise traders make trading decisions according to sentiment or mood, changes in sentiment or mood lead to more noise trading, greater mispricing, and excessive volatility (Black, 1986). Therefore, we test the noise trading channel by identifying the impact of pandemic-induced fear on realized volatility. We employ the linear volatility predictive regression in Eq. (12) following Paye (2012):

$$\log \sqrt{RV_{t+1}} = \beta_0 + \beta_1 PIF_i + \beta_2 EPU + \sum_y \gamma_y \log \sqrt{RV_{t-y}} + \epsilon_{i,t}, i = 0, 1, 2, \ldots.$$  \hspace{1cm} (12)

The second channel is the liquidity boosted or restrained by irrational investors. Baker and Stein (2004) indicate that high liquidity is a symptom of the fact that the market is dominated by irrational investors, implying that prices are overvalued or undervalued. In terms of the COVID-19 pandemic, irrational investors overreact to the information contained in the pandemic, which restrains liquidity on subsequent trading days. Liquidity is also one of the traditional proxies of sentiment (Baker & Wurgler, 2006). The relationship between pandemic-induced fear and liquidity is also helpful in understanding the information in PIF. We consider the following regression specification:

$$TURN_{t+k} = \beta_0 + \beta_1 PIF_i + \sum_y \gamma_y \text{Control}_i + \epsilon_{i,t+k}, k = 0, 1, 2, 3, 4, 5.$$  \hspace{1cm} (13)

We first examine the impact of the PIF index on realized volatility (Table 5). The lag length $i = 0, 1, 2, 3, 4$ and EPU are included as

Table 5
Pandemic-induced fear and stock market volatility.

| PIF | RET$_{t+1}$ | RET$_{t+2}$ | RET$_{t+3}$ | RET$_{t+4}$ | RET$_{t+5}$ | RET$_{t+10}$ |
|-----|-------------|-------------|-------------|-------------|-------------|-------------|
|    | 0.012*** (0.003) | 0.011*** (0.003) | 0.014*** (0.003) | 0.018*** (0.003) | 0.019*** (0.003) | 0.008** (0.003) |
| Control | YES | YES | YES | YES | YES | YES |
| Adj-R$^2$ | 11.639% | 29.504% | 35.768% | 38.515% | 39.476% | 43.428% |

Notes: This table reports the predictability of realized volatility from the pandemic-induced fear as in Eq. (12). Cons. denotes the constant, and Adj-R$^2$ denotes the adjusted-R$^2$. The Amihud and Hurvich (2004) reduce-bias estimation method is utilized. The numbers in parentheses are standard errors. *** and * denote 1%, 5% and 10% significant level, respectively.
Notes: This table reports the impact of the pandemic-induced fear on turnovers as in Eq. (13). Cons. denotes the constant, and Adj-R² denotes the adjusted-R². The Amihud and Hurvich (2004) reduce-bias estimation method is utilized. The numbers in parentheses are standard errors. ***, ** and * denote 1%, 5% and 10% significant level, respectively.

control variables. When \( i = 0, 1, 2, 3, 4 \), the impact of the PIF index on realized volatility is always positively significant. For example, the estimated coefficient of PIF is 0.008 at the 5% significance level, and the adjusted \( R^2 \) statistic is 43.427% when the realized volatility of the past 5 days is included. Pandemic-induced fear has a powerful predictive ability for future stock market volatility. The noise investors in the Chinese stock market adjust their asset allocations based on the fear resulting from the COVID-19 pandemic, which leads to higher stock volatility and lower stock returns.

Next, we investigate the impact of the PIF index on turnover, which is a proxy of liquidity. The estimation results for Eq. (12) are reported in Table 6. Notably, the impact of the PIF index on turnover is insignificant at any level. The predictive ability of pandemic-induced fear is not from the liquidity channel. We also consider an additional test using the pairwise Granger causality test among PIF, realized volatility, and turnover. Based on the AIC, the optimal lag length for Granger causality is 2. The pairwise Granger causality test results are shown in Table 7. The causality relationship between fear and turnover is rejected. Meanwhile, fear Granger causes RV, and the relationship between RV and turnover is bidirectional. Our results demonstrate that pandemic-induced fear directly affects stock returns through noise trading and confirm the conclusion that the information in the PIF index does not overlap with that in traditional sentiment proxies.

5. Robustness checks and discussions

5.1. Search behaviors of investors and alternative fear index

The National Health Commission of the People’s Republic of China announces newly reported, suspected, and death cases of COVID-19 every day, which produces strong anxiety and panic. With everyday government reports, investors acquire this information without engaging in any search behaviors. Therefore, we cannot identify whether stock returns are affected by fear based on Internet searches or by fear based on government reports. Including the CASE variable in Eq. (9) is almost helpful in alleviating such a concern. In this subsection, we provide further evidence to show that investors’ search behaviors are endogenous to the COVID-19 pandemic following Da et al. (2015). We use the following specification:

\[
PIF_{i,t+k} = \beta_0 + \beta_1 \text{CASE}_{i,t} + \beta_2 \text{EPU}_{i,t} + \epsilon_{i,t+k}, \quad k = 0, 1, 2, 3, 4, 5.
\]

The estimation results are reported in Table 8. In Panel A, we find that CASE has a significant impact on future fear when \( k = 1 \) with an estimated coefficient of 0.207 at the 5% significance level. Such results illustrate that cases released by government reports make investors concerned about the future spread of the pandemic, and investors subsequently search for pandemic-related keywords. We confirm that pandemic-induced fear is endogenous to the COVID-19 pandemic, and the results in Panel B show the robustness of our results.

We also use an alternative measure of the cases—the Pandemic Fear Index (PFI) of China, which is constructed using the newly reported and death cases following Salisu et al. (2020) and Salisu and Akanni (2020). The index considers the incubation period for COVID-19. The estimation results are shown in Panel C. However, we find that PFI does not have a significant impact on pandemic-induced fear. The Pandemic Fear Index using cases may not be suitable for China, which confirms the results in Panel A of Table 8.

Furthermore, Table 2 shows that the number of newly reported, suspected, and death cases (CASE) does not have a significant impact on the cumulative stock market returns. Considering the results of Tables 2 and 8 together, we conclude that the fear triggered by the COVID-19 pandemic, rather than the “fundamental” consequence of the pandemic (reported cases and deaths), determines future stock market returns. It is reasonable to conjecture that investors may have three different habits of obtaining information. Some only capture information related to the pandemic in daily released government reports. Some search for more information through the
Table 7
Granger causality tests for sentiment, realized volatility and turnover.

| Variables | Null hypothesis | F-statistics | p-value |
|-----------|-----------------|--------------|---------|
| TURN/PIF  | TURN does not Granger cause PIF | 0.995 | 0.372 |
| PIF does not Granger cause TURN | 0.050 | 0.952 |
| RV/PIF    | RV does not Granger cause PIF | 0.386 | 0.680 |
| PIF does not Granger cause RV | 15.750 | 0.000 |
| RV/TURN   | RV does not Granger cause TURN | 2.450 | 0.090 |
| TURN does not Granger cause RV | 2.358 | 0.098 |

Notes: This table reports pairwise Granger causality tests for the pandemic-induced fear, realized volatility and turnover.

Table 8
Search behaviors of investors.

Panel A: Pandemic-induced fear and the pandemic

| Variables | Null hypothesis | F-statistics | p-value |
|-----------|-----------------|--------------|---------|
| CASE_t   | CASE does not Granger cause PIF | 0.135 (0.088) | 2.077*** (0.084) |
| PIF does not Granger cause CASE | 0.116 (0.083) | 0.063 (0.075) |
| Cons.    | CASE does not Granger cause PIF | 0.073 (0.058) | 0.079 (0.053) |
| Adj-R²   | CASE does not Granger cause PIF | 5.167% | 8.023% |

Panel B: Pandemic-induced fear and the pandemic for longer lags

| Variables | Null hypothesis | F-statistics | p-value |
|-----------|-----------------|--------------|---------|
| CASE_t   | CASE does not Granger cause PIF | 0.155* (0.082) | 0.156* (0.080) |
| EPU_t    | EPU does not Granger cause CASE | 0.016 (0.073) | 0.073 (0.073) |
| Cons.    | CASE does not Granger cause PIF | 0.054 (0.052) | 0.054 (0.052) |
| Adj-R²   | CASE does not Granger cause PIF | 7.782% | 6.419% |

Panel C: Pandemic-induced fear and the Pandemic Fear Index

| Variables | Null hypothesis | F-statistics | p-value |
|-----------|-----------------|--------------|---------|
| PIF_t    | PIF does not Granger cause PIF | -0.020 (0.005) | 0.006 (0.004) |
| EPU_t    | EPU does not Granger cause CASE | 0.001 (0.002) | 0.001 (0.002) |
| Cons.    | CASE does not Granger cause PIF | 0.002 (0.002) | 0.003 (0.004) |
| Adj-R²   | CASE does not Granger cause PIF | -1.061% | 3.801% |

Notes: This table reports the impact of cases on the pandemic-induced fear as in Eq. (14). Cons. denotes the constant, and Adj-R² denotes the adjusted-R². The Amihud and Hurvich (2004) reduce-bias estimation method is utilized. The numbers in parentheses are standard errors. ***, ** and * denote 1%, 5% and 10% significant level, respectively.

Internet after seeing the government reports. Others directly obtain information through Internet search behaviors. Frank and Sanati (2018) indicate that retail investors are known to have attention biases and do not always pay attention to stock market information. When they search for information, they tend to pay excessive attention to the pandemic and overreact to the related information. Therefore, Internet search behaviors or habits enhance the pricing role of pandemic-induced fear. Pandemic-induced fear can also be considered a measure of sentiment induced by global health crises following Chen et al. (2020) and González-Fernández and González-Velasco (2020). The measure of pandemic-induced sentiment is driven by Internet search behaviors or habits. The theories of investor sentiment in Qiu and Welch (2004) and Da et al. (2015) indicate that investor sentiment can be endogenous to macroeconomic news and events. Therefore, pandemic-induced fear is not a measure of investor sentiment. In fact, Qiu and Welch (2004) and Da et al. (2015) indicate that investor sentiment can be endogenous to macroeconomic news and events. The theories of investor sentiment in Qiu and Welch (2004) confirm that our pandemic-induced sentiment should be expected as a measure of investor sentiment.

5.2. Newey-West HAC robust standard errors

We use the Amihud and Hurvich (2004) reduced-bias estimation approach to investigate the impact of pandemic-induced fear on the Chinese stock market. In this subsection, we apply the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) robust standard errors in the estimations. The estimation results in Table 9 confirm the robustness of the results in Section 4 from an econometric perspective.

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12 We regress the PIF index on CASE following the model $PIF_t = \beta_0 + \beta_1 CASE_t + \epsilon_t$ and decompose the PIF index into two components: the first is the fear index driven by government reports (estimated $PIF_t$), and the second is the fear index driven by search behavior (residuals $\epsilon_t$). We then consider the impact of the two components on cumulative stock returns, respectively. The results confirm that Internet search behaviors or habits enhance the impact of the PIF index.
We further reveal that pandemic-induced fear affects stock returns through the noise trading of irrational investors. More interestingly, we observe that fear or negative sentiment driven by deaths has a negative and significant impact on Chinese stock market returns, and the impact is persistent. The fear mood induced by the pandemic and investigate the impact of fear on Chinese stock market returns. A reduced-bias estimation approach for multivariate Amihud, Y., & Hurvich, C. M. (2004). Predictive regressions: A reduced-bias estimation method. Estimation results based on Newey-West HAC robust errors. Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as limits to arbitrage: Understanding the low volatility anomaly. Financial Analysts Journal, 67, 54-58.

### Table 9

**Panel A: Cumulative stock market return forecasting with control variables**

|          | RET$_{1:1+1}$ | RET$_{1:1+2}$ | RET$_{1:1+3}$ | RET$_{1:1+4}$ | RET$_{1:1+5}$ | RET$_{1:1+10}$ |
|----------|---------------|---------------|---------------|---------------|---------------|---------------|
| PIF$_t$  | -0.396 (0.348)| -0.799 (0.520)| -1.260* (0.642)| -1.358** (0.533)| -1.227** (0.502)| -1.554*** (0.586)|
| EPU$_t$  | -0.054 (0.197)| 0.052 (0.261) | 0.273 (0.329) | 0.210 (0.347) | 0.036 (0.353) | 0.491 (0.644) |
| RV$_t$   | 8.570 (21.244)| 26.045 (25.858)| 46.157 (34.637)| 25.542 (41.407)| 35.389 (34.400)| 17.699 (48.730)|
| CASE$_t$ | 0.159 (0.203) | 0.176 (0.330) | 0.082 (0.331) | 0.203 (0.404) | 0.469 (0.377) | 0.524 (0.431) |
| RET$_t$  | 0.097 (0.100) | 0.133 (0.147) | 0.203 (0.197) | 0.063 (0.230) | 0.159 (0.272) | -0.031 (0.231)|
| TURN$_t$ | -0.247 (0.474) | -0.693 (0.846) | -1.431 (0.976) | -1.992* (1.179) | -2.984** (1.271) | -6.181*** (1.740) |
| Cons.    | 0.222 (0.361) | 0.511 (0.665) | 1.020 (0.797) | 1.859* (0.973) | 2.733** (1.127) | 6.209*** (1.854) |
| Adj. $R^2$ | 0.633% | 3.680% | 9.061% | 8.443% | 9.699% | 17.389% |

**Panel B: Stock market return forecasting with control variables**

|          | RET$_t$ | RET$_{t-1}$ | RET$_{t-2}$ | RET$_{t-3}$ | RET$_{t-4}$ | RET$_{t-5}$ |
|----------|---------|-------------|-------------|-------------|-------------|-------------|
| PIF$_t$  | -0.186 (0.136) | -0.404 (0.258) | -0.459* (0.276) | -0.106 (0.208) | 0.091 (0.160) |
| EPU$_t$  | 0.274 (0.254) | 0.111 (0.184) | 0.198 (0.195) | -0.046 (0.175) | -0.185 (0.198) |
| RV$_t$   | -76.481*** (18.076) | 17.294** (8.496) | 20.257 (12.722) | -21.877* (12.484) | 10.389 (15.194) |
| CASE$_t$ | -0.236 (0.210) | 0.018 (0.174) | -0.088 (0.144) | 0.132 (0.208) | 0.236 (0.165) |
| RET$_t$  | 0.033 (0.095) | 0.073 (0.100) | -0.155* (0.084) | 0.101 (0.082) | 0.103 (0.082) |
| TURN$_t$ | 1.134 (0.703) | -0.438 (0.479) | -0.755** (0.380) | -0.554 (0.428) | -0.991*** (0.465) |
| Const.   | -0.103 (0.477) | 0.282 (0.371) | 0.529* (0.308) | 0.858** (0.364) | 0.862* (0.373) |
| Adj. $R^2$ | 18.028% | 0.083% | 2.928% | 2.500% | 1.720% |

**Panel C: Univariate stock market return forecasting with control variables**

|          | RET$_t$ | RET$_{t-1}$ | RET$_{t-2}$ | RET$_{t-3}$ | RET$_{t-4}$ | RET$_{t-5}$ |
|----------|---------|-------------|-------------|-------------|-------------|-------------|
| PIF$_t$  | -0.187 (0.120) | -0.408 (0.296) | -0.314 (0.199) | -0.492* (0.256) | -0.414 (0.252) | 0.091 (0.163) |
| Const.   | 0.087 (0.121) | 0.104 (0.118) | 0.105 (0.119) | 0.123 (0.119) | 0.135 (0.121) | 0.137 (0.125) |
| Adj. $R^2$ | 0.204% | 3.494% | 1.803% | 5.438% | 3.741% | -0.435% |

Notes: This table reports the estimation results for Eq. (9). Cons. denotes the constant, and $Adj. R^2$ denotes the adjusted-$R^2$. The numbers in parentheses are standard errors are Newey and West (1987) HAC robust standard errors. ***, ** and * denote 1%, 5% and 10% significant level, respectively.

### 6. Conclusions

We construct a pandemic-induced fear index using the Internet search volumes for keywords closely related to the COVID-19 pandemic and investigate the impact of fear on Chinese stock market returns. A reduced-bias estimation approach for multivariate regressions is employed to address the small-sample bias studied in Amihud and Hurvich (2004). We find that pandemic-induced fear has a negative and significant impact on Chinese stock market returns, and the impact is persistent. The fear mood induced by the pandemic or global health crisis is different from traditional sentiment proxies. We further reveal that pandemic-induced fear affects stock returns through the noise trading of irrational investors. More interestingly, we observe that fear or negative sentiment driven by the pandemic plays a more important role in predicting stock returns than do economic fundamentals or the number of cases and deaths.

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### Declaration of Competing Interest

None.

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