Impact of COVID-19 pandemic on risk transmission between googling investor’s sentiment, the Chinese stock and bond markets

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Abstract
Purpose – The main objective of this paper is to investigate whether the investors’ behavior under optimistic (pessimistic) conditions has an impact on risk transmission between the Chinese stock and bond markets and the sector indices mainly during the COVID-19 pandemic.

Design/methodology/approach – This study uses a new measure of the investor’s sentiment based on Google trend to construct a Chinese investor’s sentiment index and a quantile causal approach to examine the causal relationship between googling investor’s sentiment and the Chinese stock and bond markets as well as the sector indices. On the other hand, the network connectedness is used to estimate the spillover effect on the investor’s sentiment and index returns. To check the robustness of the study results, the authors employed the Chinese VIX, as another measure of the investor’s sentiment using daily data from May 2019 to December 2020.

Findings – In fact, the authors found a dual causality between the investor’s sentiment and the financial market indices in optimistic or pessimistic situations, which indicates that positive and negative financial market returns may have an effect on the Chinese investor’s sentiment. In addition, the results indicated that a pessimistic investor’s sentiment has a negative impact on the banking, healthcare and utility sectors. In fact, the study results provide a significant peak of connectivity between the investor’s sentiment, the stock market and the sector indices during the 2015–2016 and 2019–2020 turmoil periods that coincide respectively with the 2015 recession of the Chinese economy and the COVID-19 pandemic.

Originality/value – This finding suggests that the Chinese googling investor’s sentiment is considered as a prominent channel of shock spillovers during the coronavirus crisis, which confirms the behavioral contagion. This study also identifies the contribution of a particular interest for portfolio managers and investors, which helps them to accordingly design their portfolio strategy.

Keywords COVID-19, China stock-bond markets, Investor’s sentiment, Google trends, Spillover index approach and quantile causal approach

Paper type Research paper

1. Introduction
The COVID-19 pandemic is not just a health crisis, but it also led to an economic slowdown as China struggles with growing debt, a cooling of domestic demand and aggressive US rates. In fact, COVID-19 is a serious virus and a growing threat to the fragile Chinese and global economy. Indeed, China’s economy dropped by 6.8% in the first quarter of 2020 compared to the year before (Vaswani, 2020). Moreover, COVID-19 epidemic is said to weaken economic growth for Chinese financial stock markets, which is considered as the epicenter of both physical and financial contagion. Therefore, during the COVID-19 pandemic, investors may worry about disruptions that can negatively affect the performance of their investment. This sentiment led them to conduct frequent research studies on the Internet to instantly detect the news affecting their portfolio performance.

In fact, news as well as Google search for the coronavirus plays a key role in informing people of the current state of the crisis, prompting investors to make decisions on the stock
market. More particularly, in times of a market crisis, investors need technology to obtain accurate and timely data. Therefore, by using high-quality data, the investors can perform rapid analyses of the decision-making in the asset management process and then react quickly to a volatile market situation.

According to the behavioral finance theory, emergencies can affect the investor’s psychological behavior, which in turn can have a large impact on the stock prices. Previous studies have shown that investor’s sentiment on the social media can be used to predict stock price movements. In fact, there are several explanations for this finding in the behavioral finance literature (see e.g. Tseng, 2006).

On the other hand, several research studies have shown that the investor’s sentiment is one of the most important factors affecting his decisions. In this context, Lee et al. (2002) affirmed that the investor’s optimism might reduce the earnings volatility while his pessimism may increase it. In fact, the investor’s sentiment refers to emotions, such as pessimism and optimism that can affect the investment decisions and, thus the asset prices, as shown by Benhabib et al. (2016) and Jitmaneeroj (2017). Moreover, the investor’s attention is another important variable to include in the equity return model, which involves the investor’s sentiment as it positively affects equity returns (Da et al., 2011) and may affect the ability to predict stock price movement and its interaction with the investor’s sentiment. More particularly, the investor’s attention as well as his awareness to whether a piece of information exists, whereas the investor’s sentiment is a biased interpretation of the type of information whether favorable or unfavorable for the asset prices (Smales, 2021a).

In the previous study, the investor’s sentiment and attention were examined separately to test their effects on the stock returns. In fact, the investor’s sentiment is measured by social media data and Google data to draw the investor’s attention.

Accordingly, this paper addresses a new approach to understand how the investor’s sentiment has affected the stock and bond markets during the recent COVID-19 pandemic and provides useful information to investors, portfolio managers and policymakers so that they can generate more accurate forecasts in order to minimize potential fluctuations in the business cycle. This work intertwines real psychological states, such as fear and panic caused by the COVID-19 pandemic, with the textual investor sentiment index, which captures the anxiety inherent in financial markets and sectors. In addition, the Chinese investors are more sensitive to different financial information, such as the decline of other financial markets. For their part, Dai and Lan (2019) used text mining technology and sentiment analysis methods to generate positive and negative sentiments at three levels and six types of investor’s sentiments. They showed that the construction of the Shanghai Composite index of equity investor sentiment can improve the forecasting accuracy of the stock index trends.

In this context, Cao et al. (2014) indicated that in China, stocks, bonds and foreign exchange markets are highly correlated as investors frequently process noise trading based on their intuition rather than on a reasonable estimate. For their part, Abdelhedi and Boujelbène-Abbes (2019) showed that the investor’s sentiment is a channel through which shocks are transmitted between the oil and Chinese equity markets.

In fact, the main objective of this paper is to investigate whether the investors’ behavior under optimistic (pessimistic) conditions has an impact on risk transmission between the Chinese stock and bond markets and the sectorial indices mainly during the COVID-19 pandemic. Increasingly, the research behavior and values, undertaken with search engines, are seen as conveying information regarding the investor’s sentiment (Burggraf et al., 2020; Nasir et al., 2019).

To the best of our knowledge, this is the first paper to have conducted a formal and robust empirical investigation on the impact of the 2019 coronavirus pandemic upon the volatility interconnection between the investor’s sentiment, the Chinese financial market and,
particularly, the sectorial indices. To achieve this goal, we first construct a novel tool to measure the Chinese investor’s sentiment, especially during the recent coronavirus pandemic.

This study uses Google Trends data to analyze the connections between the available information of the real events and irrationality (such as expectation based on feelings) and financial markets (as a proxy for the real economy). More particularly, we investigate whether financial market and sectors are likely to benefit (or suffer) from a positive (or negative) investor’s sentiment during the pandemic.

In fact, Google search for the coronavirus plays a key role in informing people of the current state of the crisis, prompting investors to make decisions on the stock market. Moreover, it investigates the causality-in-quantile approach to identify the causal relationship between the investor’s sentiment and the index returns at different quantiles. More specifically, the higher the quantiles in our sample can be interpreted as “winners” (“appreciation”), the lower the quantiles can be seen as “losers” (“depreciation”). In addition, the importance of the Granger causality in the quantile is motivated by its importance for risk management and portfolio diversification (Hong et al., 2009) and the robustness properties of the conditional quantile. Third, we proceed to assess the impact of the COVID-19 pandemic on the connectivity between markets. Our contribution to such an understanding consists in carrying out a detailed study of the connectedness between the investor’s sentiment and the returns of financial markets and sectors over the 2012/2020 period, which includes all the phases of the great depression in China. In fact, our analysis and results range from static to dynamic connectivity. Following this logic, we use the generalized spillover index developed by Diebold and Yilmaz (2012, 2014), which is a popular method used to measure the total interdependence or connectedness in a dynamic system of random variables.

This study also contributes to the extant literature in many ways. In fact, motivated by studies on behavioral finance, we frame the role of shocks to investor sentiment on financial markets and sectors. We first introduce a recent proxy for the measurement of the Chinese investor’s sentiment using Google search queries. This article addresses a real psychological event such as the panic induced by the COVID-19 pandemic, with an investor’s sentiment index that captures the anxiety embedded in the financial markets and industry. The information discovery hypothesis seems to offer a better rationale for the results portrayed in our empirical analysis. More particularly, retail investors are using Google search to better understand the coronavirus pandemic and its effect on the Chinese stock and bond markets and five selected sector indices; it explores the responsiveness of each industry to the pandemic.

Second, we study the causality in the quantile relationship between the investor’s sentiment, the returns of financial markets and the sector indices, which enables us to investigate the impact of pessimistic and optimistic sentiment on the Chinese financial market, mainly during the COVID-19 pandemic. Third, we investigate the directionality and dynamic connectedness among the different asset classes and the investor’s sentiment, which provides an alternative way to check the contagion effect. Finally, we examine the impact of the pandemic on the spillover connectedness among the investor’s sentiment, the stock and bond markets and the sector indices. In fact, identifying the channel that plays a leading role in the risk transmission by detecting the mechanisms of risk propagation through each market during the coronavirus pandemic is essential for an effective risk management and portfolio diversification. Hence, our methods help us to characterize the timing and evolution of the key aspects of the COVID-19 crisis. To the best of our knowledge, this is the first paper to explore this.

The remainder of this paper is organized as follows. Section 2 reports a review of the related literature, section 3 discusses the data set and the applied methodology, Section 4 presents the empirical results and finally, the last section concludes the paper.
2. Literature review

An increasing number of studies are focusing on the interaction between financial markets and the investor’s sentiment. Moreover, a great number of the existing research studies support the idea that the investor’s sentiment plays an important role in explaining financial market dynamics. For example, Fang et al. (2018) examined the long-term relationship between the investor’s sentiment in the stock and bond markets. They found that the investor’s sentiment index is positively correlated with the market volatility. In fact, according to Bu and Li (2014), the sentiment index is a good predictor of the Chinese stock returns. On the other hand, Aggarwal and Mohanty (2018) investigated the impact of the investor’s sentiment index on the Indian stock market and discovered a positive correlation between the stock returns and the investor’s sentiment.

Furthermore, Gao and Lin (2018) stated that the link between the investor’s sentiment and the Chinese government bonds can be considered as a predictor of the risk premium. In fact, an excessive optimism on the stock market will spill over into the bond market where rational investors will hedge against the risk of a bubble, both of which increase the demand for bonds (Lee and Kim, 2019). For their part, Zhou et al. (2018) indicated that government intervention plays an important role in the relationship between the investor’s sentiment and the bond markets in China, which implies that when the government intervenes, the relationship between investor’s sentiment and the bond markets becomes insignificant. On the other hand, Wang et al. (2019) argue that with the investor’s sentiment, the Chinese equity and corporate bond markets are moving in the same direction. In addition, some evidence is provided to support the idea that market performance can influence the investor’s sentiment in China. As for He et al. (2019), they found that the investor’s sentiment is a systematic factor in affecting the prices. Moreover, excess returns are linked to emotional change over the same period, which affects the return volatility.

More specifically, the COVID-19 pandemic has been one of the most economically costly pandemics in recent history. In fact, several studies showed that its negative impact on the stock market has increased the difficulty of preventing and controlling risks (Guidolin et al., 2019; Laura et al., 2016; Narayan and Phan, 2020). For his part, Sansa (2020) analyzed the effect of COVID-19 on the financial markets of China and the USA. The results revealed that there is a significant positive relationship between the confirmed cases of COVID-19 and the financial markets.

However, there is little industry-level research on the effect of COVID-19 on the stock prices in the existing literature, and there are industry limitations on the economic level of COVID-19 (Iyke, 2020a; Reilly, 2020; Saadat et al., 2020). For their part, Sharif et al. (2020) analyzed the connectedness between the oil price shock, the stock market, the geopolitical risk and the economic policy uncertainty in the USA during the COVID-19 pandemic. In fact, their results showed that COVID-19 outbreak has a greater effect on both the US geopolitical risk and the economic uncertainty. They also showed that COVID-19 pandemic affects oil prices, which may be explained by the imposed travel restrictions.

While some studies have recently addressed the association between COVID-19 sentiment and returns, Samuel et al. (2020) have investigated the coronavirus potential impact on the public sentiment and discovered that COVID-19 infection has resulted in strong emotions as well as emotional and mental health difficulties.

Moreover, several studies have previously adopted Google Search Volume (GSV) to examine the effect of the investor’s attention and sentiment on the financial markets during the coronavirus pandemic. For his part, Smales (2021a) analyzed the relationship between the investor’s attention and the global market returns during the COVID-19 pandemic using the GSV as a proxy for the investor’s attention. He found that as the investor’s attention increases, the price volatility increases while the stock returns decrease. In fact, these results may be explained by the fact that during the COVID-19 health crisis, retail investors are most
likely to search for information online in order to avoid household uncertainty. Moreover, Smales (2021b) examined the relationship between the investor’s attention and stock returns across 11 sectors during this unusual period, using GSV. The author also examined that the heightened attention of investors negatively influenced US stock returns for the S&P 500 and for all individual sectors. On the other hand, Hu et al. (2021) demonstrated that the investor’s attention has an effect on level stock return co-movements and the market level, either increasing or decreasing. They found that jackpots associated with decreased attention, and, consequently, the stock return co-movements with the market decrease rather than increase.

Liu (2021) investigated the Chinese influence on the financial markets in Australia, such as the stock exchanges, the government bond markets and the foreign exchange markets, using Google Trends search results. They find that the effects of concerns over the Chinese influence are related mainly to the increased volatility of the stock market indices and the government bond yields and downward pressure on the stock prices of individual companies with significant exposure to the Chinese markets. On the other hand, Baker et al. (2020) assessed potential explanations for the unprecedented stock market response to the COVID-19 pandemic, using text-based methods to develop these points with respect to the large daily stock market. In fact, the authors found that the US stock market reacts much more forcefully to COVID-19 than in previous pandemics of 1918–1919, 1957–1958 and 1968.

Although previous studies have taken into account the relationship between the investor’s sentiment and the market returns, few studies paid attention to the role of the investor’s sentiment on risk transmission between the financial markets and other sectors during the 2019 coronavirus crisis. Therefore, the question that should be raised is what investors and analysts should do in health pandemic situations. In order to answer this question, this article investigates the effect of the COVID-19 pandemic on the dynamics of volatility connectedness between the investor’s sentiment and the financial market returns with a particular attention to the sectoral indices.

3. Methodological approach
Our empirical analysis seeks to address an important research question, namely whether the investor’s sentiment affects the dynamics of the financial markets and sectors during the COVID-19 pandemic; if so, is this effect heterogeneous? How COVID-19 drives the spillover connectedness among the markets? Therefore, the methodology used in this study is divided into three phases: First, we measure the investor’s sentiment based on the search volume obtained from Google Trend in China, so GSV provides a direct and timely measure of information acquisition. Second, we investigate the Granger causality in quantiles to describe the causal relationship between the investor’s sentiment in the financial market and the returns in other financial markets. More particularly, we are trying to find out if the market returns will be affected when the investor’s sentiment is at different levels. Finally, the method proposed by Diebold and Yilmaz (2012) is used to observe the spillover effect between investor’s sentiment, the stock-bond markets and the sector indices. More specifically, we apply Diebold and Yilmaz’s Connectedness Index to measure the static and dynamic connectedness of the investor’s sentiment and financial markets during the COVID-19 pandemic.

3.1 The construction of the Chinese googling investor’s sentiment index
3.1.1 Google Search Volume Index (GSVI). In fact, Google is the world’s most popular search engine, which provides the Google Search Volume Index (GSVI) of search terms through its product Google Trends, which shows the volume of search queries on a particular topic as a
proportion of all search features in a particular place and time period. In fact, the GSV is normalized to fall within a range of 0–100, where 100 indicates a particularly active search query. Moreover, Google Trends applies filters to remove duplicate and very rare searches. The key to building a Google-based sentiment index is identifying an appropriate list of sentimental search terms. While our study uses GSV as a proxy for the investor’s sentiment. In fact, we have adopted the approach proposed by Da et al. (2015) to construct monthly investor’s sentiment indices (ISent) for the China’s stock markets. This index is based on household Google search behavior through Google trends. In fact, this method is considered by several studies, such as those of Gao et al. (2016), Dimpfl and Kleiman (2016) Trichilli et al. (2018) and Khan and Ahmad (2018), as an appropriate measure that reflects the investor’s sentiment. The reason for using such a direct measurement is the availability of high-frequency data.

On the other hand, to construct monthly sentiment indices for China, we have selected a set of 149 finance words from the widely used Harvard IV-4 dictionary and the Lasswell value dictionary (Tetlock, 2007). Since we are interested in the local household search activities, we translated these English words into Chinese by using Google Translate. For example, the word “coronavirus” is translated into Chinese as “新 冠 病 毒.” This keyword is chosen because it is specific to our sampling period.

Moreover, to label the search terms with positive or negative sentiment and identify how these search terms are relevant to the market returns, we make the market data speak for themselves. More specifically, we contend that the news that uses at least one of our predetermined positive (negative) words raises positive (negative) optimistic (pessimistic) thoughts in the minds of the readers, which subsequently affects how the readers feel about the stock markets and the economy in general.

3.1.2 Google-based sentiment index. The final step in the construction of the Google-based sentiment index consists in identifying search terms that are the most important for returns. To make the final list of terms comparable and to account for outliers, seasonality and heteroskedasticity in the data, several other transformations were performed: First, to mitigate any concern about outliers, we winsorize each series at the 5% level (2.5% in each tail). Next, we tested for the presence of intra-annual seasonality by performing 105 unidirectional analyses of the variance (ANOVA) tests [1]. Finally, to account for any heteroskedasticity in the data and make the time series comparable, we standardized each of them by the SD of the time series.

Because it was simpler to interpret the time series, we used the GSVI logarithm, denoted by SVI for each search. Then, we downloaded the monthly SVI of search terms to our sample period from January 2012 to December 2020. Then, we calculated the monthly changes in the SVI (ΔSVI) for each search term. We eventually obtained the adjusted monthly changes in the search volume (ΔASVI). Moreover, we accounted for both positive [2] and negative [3] terms in forming our sentiment indices then, we constructed our sentiment indices by averaging the ΔASVI of the top 30 positive and 30 negative search terms for every month and calculated the difference between them as the measure of the Chinese investor’s sentiment:

$$\text{sentiment} = \sum_{i=1}^{30} R^i + (\Delta ASVI_i) - \sum_{i=1}^{30} R^i - (\Delta ASVI_i)$$

(1)

where $\sum_{i=1}^{30} R^i \pm (\Delta ASVI_i)$ represents the $t$-statistics-weighted average of the top 30 positive and negative search items, respectively. Given the dispersion of the investors’ beliefs (e.g. Diether et al. (2002)), our index measures the net effect of the investor’s sentiment on the financial markets.
3.2 Quantile Granger causality test

We study the nonlinear causality between the financial markets (sector indices) \( A(t) \) and the investor’s sentiment \( B(t) \). Based on the work of Jeong et al. (2012), the quantile-based causality may be defined as:

\[
B_t \text{ does not cause } A_t \text{ in the } \theta \text{th quantile with respect to } \{A_{t-1}, \ldots, A_{t-p}, B_{t-1}, \ldots, B_{t-q}\} \text{ if} \\
\varphi_{\theta \delta}(\delta|A_{t-1}, \ldots, A_{t-p}, B_{t-1}, \ldots, B_{t-q}) = \varphi_{\theta}(\delta|A_{t-1}, \ldots, A_{t-p})
\]

(2)

\( B_t \) may be assumed to cause \( A_t \) in the \( \delta \) th quantile respective to \( \{A_{t-1}, \ldots, A_{t-p}, B_{t-1}, \ldots, B_{t-q}\} \) if

\[
\varphi_{\theta \delta}(\delta|A_{t-1}, \ldots, A_{t-p}, B_{t-1}, \ldots, B_{t-q}) \neq \varphi_{\theta}(\delta|A_{t-1}, \ldots, A_{t-p})
\]

(3)

where \( \varphi_{\theta \delta}(\delta) \) is the \( \delta \) th quantile of \( \{ A, B \} \), which depends on \( t \) and \( 0 < \theta < 1 \).

To uncover a more nuanced causal relationship that accounts for the different quantiles, we conduct the noncausality test in the quantiles proposed by Chuang et al. (2009) given by:

\[
\varphi_{\theta \delta} = (\delta|(A, B)_{t-1}) = \varphi_{\theta \delta}(\delta|(B_{t-1})) \quad \forall \delta \in [a, b]
\]

(4)

where \( (\delta|(A, B)_{t-1}) \) denotes the \( \delta \)th quantile of \( \varphi_{\theta \delta}(\delta|(B_{t-1})) \); however, \( B_t \) does not Granger cause \( y_t \) in the quantile interval \([a, b]\) if Eqn (4) holds.

We can also conduct the Granger noncausality test in quantiles by employing the usual quantile regression method proposed by Koenker and Bassett (1978). We also tested for the presence of noncausal relation in quantiles between the stock-bond returns (sectors) and the investor’s sentiment:

\[
S_t = \alpha_0(\delta) + \sum_{i=1}^{p} \alpha_i(\delta)S_{t-i} + \sum_{j=1}^{q} \beta_j(\delta)E_{t-j} + \varepsilon_{S,t}
\]

(5a)

\[
E_t = \gamma_0(\delta) + \sum_{i=1}^{p} \gamma_i(\delta)S_{t-i} + \sum_{j=1}^{q} \theta_j(\delta)E_{t-j} + \varepsilon_{E,t}
\]

(5b)

where \( S_t \) and \( E_t \) represent the investor’s sentiment and the financial markets (sector index), respectively.

then, \( \rho_{\delta}(\varepsilon_{it}) \) is called a check function (Koenker, 2005). In fact, for any, \( \delta \in (0, 1) \) a check function is defined as:

\[
\rho_{\delta}(\varepsilon_{it}) = \begin{cases} 
\tau \varepsilon_{it} & \text{if } \varepsilon_{it} \geq 0 \\
(\delta - 1)\varepsilon_{it} & \text{if } \varepsilon_{it} < 0
\end{cases}
\]

In fact, for fixed \( (\delta) \in (0, 1) \), Chuang et al. (2009) provide the Wald statistics of the null hypothesis \( H_0 = \beta(\delta) = 0 \) given by:

\[
W_T(\delta) = \frac{T\beta(\delta)'(R\hat{\omega}^{-1}_{zz}R')\beta(\delta)}{|\delta(1 - \delta)|}
\]

(6)

where \( R \) is a \( q \times k \) selection matrix such that \( R\theta(\delta) = \beta(\delta) \), then, \( \hat{\omega}(\delta) \) is a consistent estimator of \( \omega(\delta) \), which is the variance–covariance matrix of \( \beta(\delta) \).

In addition to considering noncausality at the fixed quantile level using the Wald test presented above, we are interested in testing noncausation in quantiles over certain quantile intervals, such as \( \delta \in [a, b] \).
For their part, Koenker and Machado (1999) showed that under suitable conditions and the null hypothesis $H_0: \beta(\delta) = 0$, $\forall \delta \in T \subset [a, b]$, the suprema of the Wald statistics have a asymptotic limit distribution as:

$$\sup W(\delta) \sim \sup \left\| \frac{X_q(\delta)}{\sqrt{\delta(1 - \delta)}} \right\|^2 \tag{7}$$

where $X_q(\delta)$ is a vector of the $q$ independent Brownian bridges, equaling $[\delta(1 - \delta)^{1/2} N(0, I_q)]$ in distribution.

In practice, we may test the null $H_0: \beta(\delta) = 0$, $\forall \delta \in [a, b]$ by the supremum of the Wald statistics as:

$$\sup - W_T = \sup W_T(\delta_i) \quad i = 1, 2, \ldots, n, \tag{8}$$

where $\delta_i \in [a, b]$ with $a = \delta_1 < \ldots < \delta_n = b$. In short, the QR provides further insights into the dynamic linkages between time series $A_t$ and $B_t$.

3.3 The Diebold–Yilmaz spillover index and connectedness measures

To investigate the volatility spillover between the Chinese stock market, the bond market and the Chinese investor’s sentiment (ISent), we used the connectedness measure introduced by Diebold and Yilmaz (2014). This measure is based on the generalized vector autoregressive model (VAR) framework (Koop et al., 1996; Pesaran and Shin, 1998), in which the forecast error variance decompositions are invariant to the ordering of the variables. Therefore, the key issue in the spillover index approach is to figure out the proportion of the Chinese stock market (SSEC), the Chinese bond market (CBET) and the sector indices (bank, energy, healthcare travel and utilities) are generated from the generalized forecast error variance decomposition of the moving average representation of the VAR model expressed in Eqn (2).

In the generalized VAR framework, the $H$-step-ahead forecast error variance $\theta^k_H(H)$ contribution is:

$$\theta^k_H(H) = \frac{\sigma^2_x \sum_{h=0}^{H-1} (e_h A_h \sum_j e_j)^2}{\sum_{h=0}^{H-1} (e_h A_h \sum_j e_j)^2}, \quad H = 1, 2, \ldots, N \tag{9}$$

where $\Sigma$ is the covariance matrix for the error vector $e$, $\sigma^2_x$ is the SD of the error term for the $i$th equation and $e_j$ is the selection vector with 1 as the $i$th element and zero otherwise.

Because we follow the Koop–Pesaran–Potter–Shin generalized VAR framework, the variance shares do not necessarily add to 1: $\sum_{j=1}^{N} \theta^j_H(H) \neq 1$. In this context, Diebold and Yilmaz (2012) proposed that $\theta^j_H(H)$ should be normalized such that the information in the directional connectedness from market $j$ to market $i$ and from sector $j$ to sector $i$ is as:

$$\tilde{\theta}^j_H(H) = \frac{\theta^j_H(H)}{\sum_{j=1}^{N} \theta^j_H(H)} \tag{10}$$

Note that, by construction, $\sum_{j=1}^{N} \tilde{\theta}^j_H(H) = 1$ and $\sum_{j=1}^{N} \tilde{\theta}^j_H(H) = N$.

The connectedness volatility indices are divided into three categories. First, the total volatility spillover for the entire sample then, the directional volatility spillover and finally, the net volatility spillovers (Table 1).

We can further decompose the directional spillovers into pairwise directional spillovers. Then, the net pairwise directional connectedness is the difference between the shocks transferred from market (sector) $i$ to all the other markets (sector) $j$, which are defined as:
then, the shocks spilled from the market (sector) to market (sector) are defined as:

\[
S_g^{ij}(H) = \frac{\theta_g^{ij}(H)}{N} \tag{15}
\]

then, the shocks spilled from the market (sector) to market (sector) are defined as:

\[
S_g^{ij}(H) = \frac{\theta_g^{ij}(H)}{N} \tag{16}
\]

Net spillover index (NET)
Spillovers transmitted by the range of the market (sector) to all the other markets (sector) received from the range of all the other markets (sector)

\[
\text{NET}_i(h) = \frac{\sum_{j=1}^{N} \theta_g^{ij}(H) - \sum_{j=1}^{N} \theta_g^{ji}(H)}{N} \times 100 \tag{14}
\]

Directional spillover index from all the other assets (FROM)
Spillovers received by the range of the market (sector) from the range of all the other markets (sector)

\[
\text{FROM}_i(h) = \frac{\sum_{j=1}^{N} \theta_g^{ij}(H)}{N} \times 100 \tag{12}
\]

Directional spillover index to all the other assets (TO)
Spillovers transmitted by the range of the market (sector) to all the other markets (sector)

\[
\text{TO}_i(h) = \frac{\sum_{j=1}^{N} \theta_g^{ij}(H)}{N} \times 100 \tag{13}
\]

Table 1. Volatility spillover indices

4. Data and descriptive statistics

4.1 Data

In this study, we have used data relative to daily and monthly prices of the Shanghai stock exchange composite (SSEC) index as the proxy of China’s stock market and the Exchange Treasury Bond (CBET) from January 1, 2012 to December 31, 2020. In addition, we have used...
closing prices of five sector indices of the Shanghai stock exchange, including the energy industry index (Energy), the medical and health industry index (Health), the utility industry index (Utilities). However, the data are about the travel and leisure industry index (travel) and the banking industry (banks). Then, the financial data are collected from the Datastream.

Therefore, to construct the Chinese investor’s sentiment, we used the monthly GSVI. Then, the items about China were extracted from Google Trends (https://www.google.com/trends/). Furthermore, to give validation to our findings, we employed daily data from the CBOE China ETF volatility index (VXFXI Index), from May 2019 to December 2020. We also used the VXFXI Index as a new indicator to measure the Chinese investor’s sentiment. In fact, we obtained data relative to the index from the Chinese Wind Financial database [4].

4.2 Descriptive statistics

Table 2 presents the basic descriptive statistics, such as the mean, median, SD, skewness, kurtosis for the variables (monthly data) used in our empirical analysis: the Chinese investor’s sentiment index (ISent), the return of Shanghai Stock Exchange Composite Index (SSEC), the treasury bond yield (CBET), the return of sectoral indices, namely banks, energy, healthcare, travel and utilities. In fact, a closer look at this table shows positive average returns for the stock-bond markets as well as for banks, health and travel sectors, but negative returns for the investor’s sentiment and energy sectors. On the other hand, the health sector presents the highest average returns followed by the banking sector while the traveling one has the highest risk as captured by the SD, followed by energy, health, banks and the stock market. Therefore, we can say that the bond market has a lower SD. However, the skewness statistics of all the variables, excepting the banking sector, are negative, indicating that they are highly skewed to the left. Moreover, the kurtosis is higher than three for all the variables, which indicates that these measures have obvious peak characteristics. On the other hand, the Jarque–Bera test strongly rejects the null hypothesis of normality distribution.

Figure 1 illustrates the path time of the Chinese stock market and bond market returns, the sector indices return and the Chinese investor’s sentiment. We can also show that the Chinese stock market and the sector indices showed greater fluctuations in 2013–2015, 2018 and 2019–2020, corresponding respectively to the 2013 China’s oil product pricing reform (market-oriented reform), 2015 the Chinese stock market crash, the 2018 China–US trade conflicts and the 2019 coronavirus. We can also note that the Chinese bond market shows a downward trend in 2013, which can be explained by the inflationary pressure and the increase of the base interest rate of China. In fact, the Chinese investor’s sentiment shows a high fluctuation mainly during the years 2015 and 2019–2020, coinciding respectively with the 2015 slowdown of the Chinese economy and the COVID-19 pandemic.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std. Dev</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque–Bera</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISent</td>
<td>0.0301</td>
<td>2.3682</td>
<td>0.0000</td>
<td>-2.2462</td>
<td>26.7651</td>
<td>2607.97</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>SSEC</td>
<td>0.0039</td>
<td>0.1870</td>
<td>-0.2568</td>
<td>0.0637</td>
<td>-0.3817</td>
<td>5.9495</td>
<td>41.6639</td>
<td></td>
</tr>
<tr>
<td>CBET</td>
<td>0.0031</td>
<td>0.0092</td>
<td>-0.0033</td>
<td>0.0022</td>
<td>0.1070</td>
<td>3.4504</td>
<td>1.10810</td>
<td></td>
</tr>
<tr>
<td>Bank</td>
<td>0.0059</td>
<td>0.2781</td>
<td>-0.1638</td>
<td>0.0628</td>
<td>0.8654</td>
<td>6.5970</td>
<td>71.1254</td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.0081</td>
<td>0.1878</td>
<td>-0.2332</td>
<td>0.0702</td>
<td>-0.3678</td>
<td>4.5779</td>
<td>13.5144</td>
<td></td>
</tr>
<tr>
<td>Health</td>
<td>0.0121</td>
<td>0.1972</td>
<td>-0.2915</td>
<td>0.0743</td>
<td>-0.5287</td>
<td>4.7818</td>
<td>19.1404</td>
<td></td>
</tr>
<tr>
<td>Travel</td>
<td>0.0011</td>
<td>0.2283</td>
<td>-0.2481</td>
<td>0.0893</td>
<td>0.1528</td>
<td>3.3996</td>
<td>1.12522</td>
<td></td>
</tr>
<tr>
<td>Utilities</td>
<td>0.0022</td>
<td>0.2308</td>
<td>-0.2740</td>
<td>0.0636</td>
<td>-0.0567</td>
<td>8.8190</td>
<td>151.0632</td>
<td></td>
</tr>
</tbody>
</table>

Note(s): ISent is the Chinese investor’s sentiment index, SSEC is the return of the Shanghai Stock Exchange Composite Index, CBET is the treasury bond yield, banks, energy, health care, traveling, utilities and the return of the sectoral indices.

Table 2. Descriptive statistics
5. Empirical results and discussion

5.1 The causality in the quantile relationship between the investor’s sentiment and the financial market indices

On the other hand, we apply the BDS test of Brock et al. (1996), which tests the null hypothesis of whiteness (independently and identically distributed series) against an unspecified
alternative, including nonwhite linear and nonlinear dependence (Table 3). The results revealed that the BDS test statistics are statistically significant in all cases, which means that there is a nonlinear relationship between the investor’s sentiment, the financial markets and the sector index. Hence, the quantile causality test is susceptible to misspecify the error probabilities.

Table 4 reports the results of the quantile causality between the investor’s sentiment and the financial markets. Then, the intervals of low quintile, such as [0.05 to 0.25], represent a period with a low ISent level (pessimistic). Accordingly, [0.75–0.95] includes a high level of ISent (optimistic).

In fact, our empirical analysis clearly indicates the existence of dual causality between the investor’s sentiment and the financial market indices in optimistic or pessimistic situations, which indicates that positive and negative financial market returns may have an effect on the investor’s sentiment. We also found that the Chinese government bonds can strongly evade the investor’s risk. This result can be explained by the fact that investors prefer government bonds rather than stocks at the time of pessimism, which raises the relative demand for government bonds. Furthermore, pessimism predicts the contraction of the real economy and shapes the expectations of the rising interest rates. Moreover, we showed significant impacts of the investor’s sentiment on the equity markets when the investor’s sentiment is in the quantiles of 0.05, 0.1, 0.25, 0.5, 0.75, 0.80 and 0.95. Consequently, the investor’s sentiment affects the Chinese stock markets in optimistic or pessimistic states. This implies that our results are in-line with previous findings that generally indicate that the current COVID-19 pandemic has a significant causal impact on the investor’s sentiment and the stock markets (e.g. Al-Awadhi et al., 2020; Liu, 2020a; Zhang et al., 2020).

However, as the investor’s sentiment in the Chinese stock market is vulnerable to bombs and unexpected shocks, the stock prices often deviate from the fundamentals (Li et al., 2014). In fact, in China, this similarity does not elicit a capitalistic interaction effect between stocks and bonds through the investor’s sentiment. On the other hand, Lin et al. (2019) showed that Chinese companies and individual investors are eager to invest in capital. Therefore, when the investor’s sentiment is relatively high, investors are more likely to be too optimistic to judge the share price (Liu, 2020b). Regarding the effects of the stock-bond markets on the investor’s sentiment, a clear bidirectional causality exists in the lower quantile levels. These results provide useful information to investors who use the stocks or bonds to hedge or manage downside or upside risks in their portfolios. Since the bond markets are the primary tool for asset allocation at different times of the business cycle, changes in the investor’s sentiment among equity may be reflected by fluctuations in the bond market. For example, Qian and Luo (2016) showed that with the depression of the macroeconomics in China, the

<table>
<thead>
<tr>
<th>Impact of COVID-19 pandemic on risk transmission</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>BDS statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISent and SSEC (2)</td>
<td>0.2299***</td>
</tr>
<tr>
<td>ISent and CBET (2)</td>
<td>0.0389***</td>
</tr>
<tr>
<td>ISent and Bank (2)</td>
<td>0.0284***</td>
</tr>
<tr>
<td>ISent and energy (2)</td>
<td>0.0001***</td>
</tr>
<tr>
<td>ISent and health (2)</td>
<td>0.0151***</td>
</tr>
<tr>
<td>ISent and travel (2)</td>
<td>0.0195***</td>
</tr>
<tr>
<td>ISent and utilities (2)</td>
<td>0.0834***</td>
</tr>
</tbody>
</table>

**Note(s):** The null hypothesis is that the residual is an independent and identical distribution. ISent, SSEC, CBET, Bank, Energy, Health Travel and Utilities represent investor sentiment in the stock market, bond market and five sector index, respectively. The number in parentheses stands for the number of (embedded) dimension, which embeds the time series into m-dimensional vectors.
<table>
<thead>
<tr>
<th>Quantile causality test investor sentiment and financial markets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: δ pair (δ, 1_δ) ISent is a dependent variable</td>
</tr>
<tr>
<td>ISent</td>
</tr>
<tr>
<td>0.06</td>
</tr>
<tr>
<td>0.1</td>
</tr>
<tr>
<td>0.25</td>
</tr>
<tr>
<td>0.50</td>
</tr>
<tr>
<td>0.75</td>
</tr>
<tr>
<td>0.90</td>
</tr>
<tr>
<td>0.95</td>
</tr>
</tbody>
</table>

Panel B: δ pair (δ, 1_δ) stock-bond indexes are a dependent variable

| ISent            | SSEC                  |
| 0.06            | -0.0202*** (-3.3340)  |
| 0.1             | -0.0079 (-1.6343)    |
| 0.25            | -0.0056 (-0.7319)    |
| 0.50            | 0.0001 (0.0164)      |
| 0.75            | 0.0028 (0.5217)      |
| 0.90            | 0.0089* (1.3626)     |
| 0.95            |                      |

| CBET             | ISent |
| 0.06            | -0.0016*** (-5.3641) |
| 0.1             | -0.0011* (-1.6722)   |
| 0.25            | -0.00138*** (-3.3167)|
| 0.50            | -0.0006 (-0.5390)    |
| 0.75            | -0.0009** (-3.3307)  |
| 0.90            | -0.0007** (-2.9679)  |
| 0.95            |                      |

**Note(s):** The sup-Wald test statistics are reported. *, **, and *** indicate the statistical significance at the 10, 5 and 1% levels, respectively.
phenomenon of “flight to quality” leads to a flight of the stock capital to the government bond market, exacerbating the pessimistic feeling of the stock market. In addition, there is no significant impact of the stock market on the investor’s sentiment. In fact, it is stated that the stock market returns are determined by the investor’s sentiment while their effect is unidirectional rather than a feedback mechanism. From this perspective, we have reasonable evidence to support the idea that the investor’s sentiment can be viewed as a systematic factor influencing the Chinese financial system.

5.2 The causal relationship between the investor’s sentiment and the sector indices
Table 5 shows the results for the quantile causality between the investor’s sentiment and the sector indices. Regarding the causality from the banking, health and utility sectors, the null hypothesis that the investor’s sentiment does not Granger cause the banking, health and utility sectors is rejected in the 0.05, 0.1, 0.25 and 0.5 quantiles. This means that the banking, health and utility sectors can be influenced only when the investor’s sentiment is at a relatively low level. This effect is channeled especially at extremely low quantiles implying that the investor’s depression contributes to economic change, especially during times of political instability and social unrest. Indeed, when investors are depressed, they tend to lose faith in future financial markets. Therefore, this sentiment can detect the investor’s behavior during the COVID-19 crisis. This implies that there is relative outperformance in the sectors the most likely to benefit from the related changes in the household and government spending (i.e. consumer staples, health and IT).

As for Yang et al. (2020), they found that the outbreak of the pandemic caused a sharp increase of risks in the financial sector, as they are transmitted to other industries. As a result, banks charged lower fees, which had a negative impact on the banking profits.

However, with regard to the energy and travel sectors, the null hypothesis that the investor’s sentiment does not cause energy in Granger cannot be rejected in all the quantiles, which means that the investor’s sentiment has no impact on the energy and travel sectors.

On the other hand, when the energy sector suffers from a sudden and unprecedented shock, like the COVID-19 pandemic, it is more than likely that it will be strongly affected. Moreover, we conclude that the impact of the investor’s sentiment on the energy sector in China has no effect.

As a by-product of our analysis, we can say that the effects of five sector indices on the investor’s sentiment are also explored. Moreover, our results indicate that when the major sectors become extremely pessimistic, the investor’s sentiment will be influenced. In fact, these sectors offer a valuable implication to the Chinese investors looking to the future of the COVID-19 pandemic, as the feeling of pessimism is playing a growing role in the amplification of the COVID-19 crisis, (e.g. Suneson, 2020).

5.3 Spillover structure between the investor’s sentiment, the stock and the bond market as well as the Chinese index sectors
In fact, Table 6 reports the connectedness-estimated parameters between the Chinese stock and bond market returns as well as the investor’s sentiment for January 1, 2012 and December 31, 2020. In fact, the diagonal values denote how investors are affected by their own feelings. On the other hand, the off-diagonal row sum is the directional sentiment spillover of investor $i$ from market $j$ (labeled “directional from others”), and the off-diagonal column sum is the directional contribution of investor $i$ to market $j$ (labeled “directional to others”). The “Net” spillover shows net transmitter and net recipients of shocks. The total volatility connectivity across the entire sample is around 6.93%, implying a low connectedness across the markets. The first value of the last row of the connectedness matrix represents the “Net connectedness” between the Investor’s sentiment and the stock-bond markets. This is simply the difference
### Table 5: Quantile Causality Test: Investor Sentiment and Sector Indexes Returns

<table>
<thead>
<tr>
<th>Panel A: δ pair (6, 1 – 8) ISent is a dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISent Bank</td>
</tr>
<tr>
<td>ISent energy</td>
</tr>
<tr>
<td>ISent health</td>
</tr>
<tr>
<td>ISent travel</td>
</tr>
<tr>
<td>ISent utilities</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: δ pair (6, 1 – 8) sector indexes are a dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank ISent</td>
</tr>
<tr>
<td>Energy ISent</td>
</tr>
<tr>
<td>Health ISent</td>
</tr>
<tr>
<td>Travel ISent</td>
</tr>
<tr>
<td>Utilities ISent</td>
</tr>
</tbody>
</table>

**Note(s):** The sup-Wald test statistics and the selected lag order (in square brackets) are reported. *, **, and *** indicate the statistical significance at the 10, 5 and 1% levels, respectively.
between “To” and “From.” This difference confirms that the investor’s sentiment is the main net transmitter of shocks and hence, it influences others more than it is influenced by them whereby stock (−1.06%) and bond (−0.01%) are the main receiver of shocks.

Therefore, to find the pairs that significantly transmit and receive shocks from each another, we have to look across the first column and the first row of Table 6. For example, the investor’s sentiment transmits the highest shocks from the bond market (6.21%), which implies that the Chinese investor’s sentiment is a net transmitter of shocks from the bond market. As for the stock market, the investor’s sentiment transmits (3.63%) of shocks while receiving only (0.37%) of them. Moreover, the results of the pairwise data indicate that the bond market has a higher effect on the investor’s sentiment. In fact, this supports the idea that the bond market, as a global market, has the most dominant effect on the investor’s sentiment.

Table 7 reports the to-connectedness, the from-connectedness and the net-connectedness between the investor’s sentiment and the Chinese index sector. The column “from” shows that all the sectors gain substantial information from the system ranging from 2.12 to 9.65%. However, their contributions to the system vary significantly as the lowest is the investor’s sentiment, with only 2.12%. This can be explained by the fact that these sectors are generally important since they represent a large part of the economic structure in China and have a high relevance with other sectors. However, the investor’s sentiment has the lowest connectivity with values of 2.12%, which indicates that the investor’s sentiment has minimal risk ripple effects on the Chinese sector indices. Moreover, by estimating the net-connectedness, we found that the investor’s sentiment, traveling and utilities are risk transmitters while healthcare, banks and energy are risk receptors. Finally, we estimate the total connectedness to uncover the average level of risk spillover within sectors. We notice that the total risk spillover score reaches 41.23%, which indicates that the Chinese sectors have a high spillover intensity.

5.4 Dynamic rolling connectedness
5.4.1 Dynamic connectedness between the investor’s sentiment and the stock-bond markets based on a rolling sample. In this section, we use a rolling window analysis to uncover the evolution of the risk spillovers within the Chinese investor’s sentiment, the stock and bond markets. The window with a fixed size of 100 days rolls from January 1, 2012 to December 31, 2020 with a step of one day. In each window, the total connectedness is estimated with the same model parameters (the lag order \( p = 2 \) and predictive horizon \( H = 10 \)) as the whole sample analysis. Figure 2 illustrates the plot of full connectivity. We can see that the total connectivity exhibits a high volatility with fluctuations between 10 and 70%. There are roughly four high-risk periods. On June 24, 2013, the total connectivity increased considerably, particularly with the shock on China’s oil product pricing reform (market-oriented reform episodes of oil supply disruptions. In fact, in 2015, total connectivity again increased considerably reaching a score of 32%. As a consequence, in 2015, the Chinese stock
<table>
<thead>
<tr>
<th>Contribution to others</th>
<th>ISent</th>
<th>Bank</th>
<th>Travel</th>
<th>Health</th>
<th>Energy</th>
<th>Utilities</th>
<th>From others</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISent</td>
<td>87.28</td>
<td>1.50</td>
<td>3.41</td>
<td>5.89</td>
<td>1.62</td>
<td>0.31</td>
<td>2.12</td>
</tr>
<tr>
<td>Bank</td>
<td>3.68</td>
<td>85.93</td>
<td>4.90</td>
<td>2.52</td>
<td>0.48</td>
<td>2.49</td>
<td>2.34</td>
</tr>
<tr>
<td>Travel</td>
<td>4.06</td>
<td>0.27</td>
<td>43.32</td>
<td>20.79</td>
<td>14.68</td>
<td>16.89</td>
<td>9.45</td>
</tr>
<tr>
<td>Health</td>
<td>5.08</td>
<td>0.70</td>
<td>22.33</td>
<td>46.37</td>
<td>10.06</td>
<td>15.46</td>
<td>8.94</td>
</tr>
<tr>
<td>Energy</td>
<td>0.87</td>
<td>0.37</td>
<td>15.99</td>
<td>7.81</td>
<td>47.59</td>
<td>27.37</td>
<td>8.74</td>
</tr>
<tr>
<td>Utilities</td>
<td>2.84</td>
<td>0.41</td>
<td>16.29</td>
<td>13.33</td>
<td>25.02</td>
<td>42.12</td>
<td>9.65</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Net contribution (To – From) Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISent</td>
</tr>
<tr>
<td>Bank</td>
</tr>
<tr>
<td>Travel</td>
</tr>
<tr>
<td>Health</td>
</tr>
<tr>
<td>Energy</td>
</tr>
<tr>
<td>Utilities</td>
</tr>
<tr>
<td>Contribution to others</td>
</tr>
</tbody>
</table>

Note(s): Full-sample interindustry index fluctuation spillover structure. The sample covers the period between January 2, 2012, and December 31, 2020 while the predictive horizon is 10 days. Then, the $i$th entry of the upper-left $10 \times 10$ firm's submatrix gives the $ij$th a pairwise directional connectedness, which means that the percentage of 10-days-ahead forecast error variance of firm $i$ is due to shocks from firm $j$. On the other hand, the “FROM” column gives total directional connectedness of from, which is the row sums. The “TO” row gives total directional connectedness of to, which is the column sums. The “NET” row measures the difference in total directional connectedness (TO – FROM). The bottom-right element “Total” is the mean of “FROM”, or equivalently, the mean of “TO”, which mirrors the total connectedness.

Net contribution (To – From) Others: 0.63 $-$ 1.80 1.04 $-$ 0.55 $-$ 0.09 0.77

Connectedness = 41.23%
markets collapsed). This suggests that risk spillovers tend to increase, which caused thousands and thousands of stocks to depreciate by 70%. As a result, many publicly traded companies have suspended trading in stocks for various reasons in order to stop the fall of prices (Mezghani and Boujelbène, 2018). In fact, in June 2018, most of the stocks fell by 10%, suggesting that there is a very high overall risk in the markets. Another reason could be that the investors' confidence has been severely affected by the seasoned share offering of listed companies. Finally, in January 2020, the total spillovers have recorded a sharp increase. In fact, during this year (2020), there has been a drastic drop in the asset quality caused by economic hardship and the Covid-19 pandemic, which are likely to cause stress in the financial markets.

On the other hand, according to Broadstock and Zhang (2019), the market sentiment reaction to the epidemic can be quickly amplified by social media, which, in turn, spurs business activity and causes extreme price movements. Therefore, the uncertainty created by the coronavirus and exacerbated by the opacity of the Chinese authorities will undoubtedly cause risk premiums in the stock and bond markets to increase and already cautious business executives to continue to sit on new investment and expansion plans. In fact, the COVID-19 pandemic has suddenly become a serious threat to the Chinese and global economies.

Figure 3 demonstrates the dynamic of total connectedness between the Chinese investor’s sentiment and the sector indices in the period from January 2, 2012 to December 31, 2020. We show that the connectivity between the sector indices and the investor’s sentiment peaked during the 2013–2014, 2015–2016 and 2019–2020 turmoil periods. On the other hand, the 2015 Ebola epidemic resulted in a strong volatility while the COVID-19 pandemic caused the sector’s volatility to increase sharply. This figure shows that this new pandemic has had harmful consequences on the public health and the economic sectors.

5.4.2 Rolling-sample net pairwise directional connectedness from the investor’s sentiment to the Chinese stock-bond markets and sector indices. Figure 4 provides the net pairwise directional spillovers from the investor’s sentiment to each stock-bond market and sector indices. We found that there is a strong volatility spillover between the assets and the investor’s sentiment, as they are all significant transmitters and receivers of shocks.

The results showed that the net pairwise directional connectedness from the investor’s sentiment to the Shanghai stock index is negative during the various periods, which indicates that the Chinese stock market is a risk receptor during the mentioned periods. This finding
suggests that investors are worried about the economic outlook because of the COVID-19 pandemic. In fact, they predict that the coronavirus will continue to spread and cause more disruption, lower demand and possibly cause a global slowdown. In addition, the results showed that during the COVID-19 epidemic, the Chinese investor’s emotions are very dependent on the returns of the bond market. This result can be explained by the fact that investors pay much attention to the bond market in order to save their wealth.

In addition, the Chinese investor’s sentiment dominates the connectivity per pair and has a significant impact on the major sectors except the health and utility sectors. Therefore, the Chinese investor’s sentiment is a net transmitter of shocks to the banking, traveling and energy sectors during the sample period. On the other hand, during the COVID-19 pandemic, the investor’s sentiment received shocks from the healthcare and utility sectors. In fact, this result is logic because the pandemic is a health crisis that increased uncertainty in the Chinese stock market. Consequently, we can conclude that the investor’s sentiment is an essential product for portfolio allocation and the hedging ability of the market contingent on the initial levels from which sentiment changes. They build on previous studies linking performance spillovers to the market uncertainty (e.g. Antonakakis et al., 2019) and economic uncertainty (e.g. Ji et al., 2019).

6. Robustness check
To give more validation to our findings, we use the CBOE China ETF Volatility Index traded at the Shanghai Stock Exchange (VXFXI Index), as a second measure of the investor’s sentiment. We also investigated the impact of the COVID-19 on the risk spillover between the Chinese implied volatility index, the stock and bond markets and the sector indices. We also studied the dynamics of the connectedness using daily data from May 2019 to December 2020. In fact, Figure 5 (a) and 5(b) report respectively the total spillover connectedness index between the VXFXI index, the stock and bond market and between the VXFXI and the sector indices. We also showed that the dynamic connectivities between China investor sentiment and financial markets are volatile, and they reached around 50% at the end of 2019. Since then, they decreased persistently but at a slow rate until the end of the 2020 where it dropped to less than 20%, which coincides with the COVID-19 outbreak in China.

Figure 6 displays the dynamic net pairwise connectedness from the VXFXI index to the stock and bond markets and each sectoral index. We found that the implied volatility index

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**Figure 3.**
Dynamic total volatility spillovers between investor’s sentiment and sector indices

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**Figure 6.**
Dynamic net pairwise connectedness from the VXFXI index to the stock and bond markets and each sectoral index.
transmits shocks to the stock and bond markets throughout the period of analysis. Moreover, the results revealed that Chinese implied volatility dominates the net pairwise connectedness and has a significant impact on the banking, traveling, energy and utility sectors during the first three months of 2020. This confirms that these sectors are net risk transmitters of risk, as
shown in Figure 4. On the contrary, at the end of 2020, the healthcare, travel and energy sectors were permanent net receivers of shocks, and hence, they were driven by the market that makes them less attractive for investors. This can be explained by the increase of the number of deaths due to the shortage of drugs, the lack of vaccines, to treat patients, the insufficient number of hospital beds and also insufficient centers of isolation caused the spread of the COVID-19 pandemic. Consequently, this result confirms previous findings suggesting that the Chinese stock market and the investor’s sentiment became more pronounced during the current COVID-19 pandemic. The influence of the pandemic is the reason behind the difference between the volatility spillover results reported in this study and those of Hussain et al. (2019).
Figure 6. Impact of COVID-19 pandemic on net pairwise directional connectedness from the VXFXI index to the stock market, bond market and sectorial indices.
7. Conclusion and policy implications
The COVID-19 pandemic has suddenly become a serious threat to the Chinese and global economies. Its severity is difficult to assess given the unknown ways of its spread and its virulence, which created opportunities for recovery and huge gains. Moreover, identifying how the shocks are transmitted from one market to another during the coronavirus crisis is essential for an effective risk management and portfolio diversification. Therefore, to extend the existing literature in this field, this paper aims mainly at analyzing the impact of the investor’s sentiment on the shock transmission between the Chinese investor’s sentiment, the stock and bond markets and the sector indices during the COVID-19 pandemic. Moreover, we used a new measure of the investor’s sentiment based on social media and Internet to construct a Chinese googling investor’s sentiment index. On the other hand, to check the robustness of our results, we employed the CBOE China’s ETF Volatility Index traded at the Shanghai Stock Exchange Market as another measure of the investor’s sentiment and daily data from May 2019 to December 2020.

Furthermore, we examined the causal relationship between the investor’s sentiment and the financial markets and also five major sectors in China then, we proceeded with the Granger causality in quantiles. In fact, our empirical analysis clearly indicates the existence of dual causality between the investor’s sentiment and the financial market indices in optimistic or pessimistic situations, which indicates that positive and negative financial market returns may have an effect on the investor’s sentiment. This finding supports the view of prior studies suggesting that the performance of the investor’s sentiment is affected by the financial markets during the bubble period (e.g. Cheema et al., 2020; Lee et al., 2002). Importantly, our results add to the results of Zhang et al. (2020), which showed that the global financial market risks strongly increased during the COVID-19 pandemic.

In sum, the rise and fall of the global financial markets will influence the investor’s sentiment perceptions and therefore affect the investor’s behavior. The findings also showed that the effect of the investor’s sentiment on the relationship between the banking, health and utility sectors is stronger mainly at the lower level of the quantile, which means that these sectors offer diversified opportunities during the investor’s sentiment pessimism.

On the other hand, using Diebold and Yilmaz spillover indexes, we examined the volatility connectedness among investor’s sentiment and financial markets indices mainly during the current COVID-19 pandemic. We also showed significant peaks of connectivity between the investor’s sentiment, the stock market and the sector indices during the 2015–2016 and 2019–2020 turmoil periods that coincided respectively with the 2015 recession of the Chinese economy and the COVID-19 pandemic.

Moreover, the dynamic net pairwise spillover showed that the Shanghai stock market index, the China’s bond market, the healthcare and the utility sectors have a net receiving behavior throughout the sample period. However, we found that during the COVID-19 pandemic, the Chinese investor’s sentiment is a net transmitter of shocks to the banking, traveling and energy sectors. Moreover, this finding suggests that googling the Chinese investor’s sentiment is considered as a prominent channel of shock spillovers during the COVID-19 pandemic, which confirms the behavioral theory of contagion (Boujelbène, 2013).

Therefore, this can help fund managers adjust their portfolio risk exposure by including stocks either in the sectors that significantly respond to the COVID-19 sentiment or those that do not. In fact, for policymakers, it is important that they strengthen their major sectors in China, especially the health sector, against exposure to risks. On the other hand, healthcare sectors have long created investment opportunities with changes in strategic direction, such as disease burden and geographic footprint and outsourcing of operations, such as manufacturing and supply chain, thus making the whole economy the target of the exposure of the health sectors to negative shocks. In fact, the network connectivity can help investors predict trends and promote their reasonable asset allocation using the investor’s sentiment
and the market response to chocks. Due to the close link between the Chinese stock and bond markets, the sector indices, the investor’s sentiment and the volatility mechanism can be useful for investors as they enable them to consider the dynamics of each market so that they can diversify their portfolios.

Notes
1. Out of the large number of methods available to account for data seasonality, we followed the two-step approach (i.e. ANOVA and multiple regressions with dummy variables) proposed by Da et al. (2015), as it is appropriate when dealing with Google-based data.
2. The list of positive terms included: stocks, consume, growth, dividends, profits, investment, entrepreneurship, partnership, influence, happiness, optimism, buying, ... etc.
3. The list of negative terms in Google Trends comprises taxes, crisis, debt, unemployment, poverty, coronavirus, panic, contagion, epidemic or pandemic virus, market crash, depression, recession, short selling, default, bankruptcy, losses, conflicts ... etc.
4. The detailed construction method of the CBOE China ETF volatility index, one can refer to the announcement issued by the Shanghai Stock Exchange, see https://www.cboe.com/micro/vix/vixwhite.pdf.

References


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