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Insights from the (in)efficiency of Chinese sectoral indices during COVID-19

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ABSTRACT
This article evaluates the effects of the crisis caused by the new Coronavirus (COVID-19) on the Chinese sectoral indices. Using the complexity–entropy plane methodology, we find that the COVID-19 crisis caused increased inefficiency in most of China’s equity sectors. We also find heterogeneous effects depending on the economic sector. Our results are useful for a better understanding the effect of global shocks on the stock markets and how their effects are distributed across economic sectors.

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1. Introduction

The crisis caused by the new Coronavirus (COVID-19) has had significant impacts on almost all countries, with adverse effects on those countries’ economies [1]. Without remedies to combat the disease, the solution found was to impose social isolation measures and the imposition of habits such as the use of masks and frequent hand hygiene [2,3].

In some countries, it was necessary to adopt temporary lockdown [4–7] in which citizens could only leave home if they found urgent needs such as the purchase of medicines or food. The effects on the different sectors of the economy can be significant. For example, sectors such as tourism [8] have suffered shocks of great magnitude with the risk of a wave of bankruptcies sweeping many companies in these sectors.

Many countries have adopted expansionary fiscal and monetary policy measures to fight these adverse effects [9]. Still, they tried to keep the credit channel working to not go into bankruptcy. Subsidized credit policies with the approval of national governments have been implemented in several economies.

In this context, a relevant research question is how the different sectors reacted to the crisis caused by the pandemic [10]. In this article, we seek to answer this question using a methodology that has not yet been applied to answer the question. We analyzed how the efficiency of the different sectors of the Chinese economy was affected by the pandemic.

The critical question concerns market efficiency. Large-scale shocks are expected to cause a significant increase in risk [11]. It is essential to assess which sectors are most resilient to these shocks and which are more likely to run into

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problems due to shocks. These issues are essential for investors and financial regulators who may need to design specific public policies.

Our contribution to the debate consists of using the Bandt & Pompe permutation entropy [12], the complexity–entropy causality plane [13], and the sliding windows technique. These methods are beneficial for assessing whether the Chinese economy’s economic sectors maintained their levels of efficiency during the pandemic.

Our results suggest that the crisis has caused an increase in inefficiency in Chinese economic sectors. This effect depends on the economic sector under analysis, which suggests that the crisis’s effects depend on the sector and are not felt homogeneously. It also suggests that it is important to assess that the different economic sectors respond differently to global shocks when creating diversified portfolios [14].

We contribute to the literature by examining Chinese sectoral indices for the period before and after the immense health and economic crisis provoked by the new Coronavirus (COVID-19). To the best of our knowledge, our paper is the first to employ the Complexity–Entropy Causality Plane to test for a change in market efficiency after this large shock. Our empirical results suggest a reduction in market efficiency in the post-shock period. We also provide evidence that the effect on the economic sectors is heterogeneous. Therefore, our contribution is empirical.

The rest of this paper is divided as follows. Section 2, present the methods. Section 3, describes the database. Section 4 performs the empirical analysis of our results. Section 5, draws our conclusions.

2. Permutation entropy, Complexity – entropy causality plane (CECP), and sliding window technique

This section describes the methods that we employ in this investigation. Specifically, it formalizes the Permutation entropy, the Complexity–entropy causality plane (CECP), and Sliding Window approach.

2.1. Permutation entropy

In the early 2000 years, Bandt & Pompe [12] proposed a robust methodology to evaluate the probability distribution of ordinal patterns [15]. Specifically, the Bandt & Pompe permutation entropy is a complexity measure that evaluates the information content and structural complexity in the underlying stochastic process.

The permutation entropy absolutely considering the temporal causality within historical data. Thus, the Bandt & Pompe permutation entropy is associated with a symbolic sequences to the segments of the time series under investigation [16], based on the existence of local orders by comparing neighboring values of the original series and employs the probability distribution function (PDF) related to these symbols, to measure the complexity quantifier [17].

In this way, let a time series denoted by \( y_q \), \( q = 1, \ldots, Q \) and regard \( Q - (d - 1) \) overlapping segments \( Y_d = (y_{q}, y_{q+1}, \ldots, y_{q+d-1}) \) of length \( d \). Within each segment, the ranking of the values are carried out based in increasing order to find the indices \( s_0, s_1, \ldots, s_{d-1} \) such that \( y_{q+0} \leq y_{q+1} \leq \ldots y_{q+s_{d-1}} \). The respective \( d \)-tuples (or words) \( \pi = (s_0, s_1, \ldots, s_{d-1}) \) correspond to the original segments. We can assume any of the \( d! \) possible permutations of the set \{0, 1, \ldots, d - 1\}. Given this, the Bandt & Pompe permutation entropy (order \( d \geq 2 \)) is:

\[
H(d) = - \sum_{\pi} p(\pi) \log p(\pi)
\]  

where \( \{\pi\} \) denoted the summation over all the \( d! \) possible permutations of order \( d \) and \( p(\pi) \) consists to the relative frequency of occurrences of the permutation \( \pi \).

The optimal \( d \) is directly associated to the underlying stochastic process. However, to stabilize the better statistical fit as a rule of thumb, the literature suggests to choose a maximum \( d \) in order to satisfy \( n > 5d! \) [18].

2.2. Complexity–entropy causality plane (CECP)

The (CECP) [13] is a two-dimensional plane (2D). It was introduced to examine the difference stochastic noise and deterministic chaotic behavior. Initially, due to its effectiveness related to the analysis of complex systems’ physical properties, the CECP was used exclusively by researchers from Information theory [18–20].

However, the CECP considers particular characteristics to a time series under analysis, such as the information contained in the data that chronologically organized form this historical data and the structural complexity of the time series and this aroused the interest of researchers from the most diverse areas such as finance [17,21], climatology [22], biomedical [23], reliability [24], and many others [20,25,26].

The central idea of the CECP consists of build-up a 2D plane. In this 2D plane, the abscissa axis represents the permutation entropy, while the Jensen–Shannon statistical complexity measure denotes ordinate axis [13] by

\[
B [P] = - \frac{K [P, U]}{K_{\max}} J_{\pi} [P]
\]

where \( J_{\pi} [P] = \frac{J [P]}{\log d} \) is the normalized permutation entropy, \( K [P, U] \) is the Jensen–Shannon divergence-based disequilibrium measure [27].

\[
K [P, U] = \left\{ J \left( \frac{P + U}{2} \right) - \frac{J [P]}{2} - \frac{J [U]}{2} \right\}
\]


Table 1
Details of the Chinese sectoral indices, sector, and index.

| Item   | Sector                          | Standard and Poor’s/IFCI China Sector Index United States Dollar |
|--------|---------------------------------|----------------------------------------------------------------|
| 1      | BANKS                           | China Banks                                                  |
| 2      | CAP_GOODS                       | Capital Goods                                               |
| 3      | AUTO_COMP                      | Auto and Components                                         |
| 4      | CONS_DISC                      | Construction Discretionary                                  |
| 5      | CONS_DURA                       | Construction Durables and Asia Pacific                      |
| 6      | CONS_STAP                      | Construction Staples                                         |
| 7      | DIV_FINAN                       | Diversified Financials                                      |
| 8      | ENERGY                          | Energy                                                      |
| 9      | FOOD_BE_TOB                    | Food Beverages and Tobacco                                  |
| 10     | FOOD_DRUG_RET                  | Food and Drug Retail                                        |
| 11     | FINAN                           | Financials                                                  |
| 12     | HC                              | Health Care                                                |
| 13     | HOUS_PERI                       | Household and Peripherals                                    |
| 14     | LEI                             | HF/HT/Leisure                                               |
| 15     | INDUSTRIALS                    | Industrials                                                 |
| 16     | IT                              | Information Technology                                      |
| 17     | INSURANCE                       | Insurance                                                   |
| 18     | MATERIALS                      | Materials                                                   |
| 19     | PHA_BIOT                        | Pharmaceuticals and Biotechnology                            |
| 20     | RETAIL                          | Retailing                                                   |
| 21     | SOFT_SERV                      | Software and Services                                       |
| 22     | SEMI_COND                      | Semiconductor                                               |
| 23     | TELE                            | Telecommunications                                          |
| 24     | TECH_HARD                      | Technology Hardware                                         |
| 25     | TRANSP                          | Transpo                                                     |
| 26     | UTILITIES                      | Utilities                                                    |

This complexity measure is employed to evaluate the difference between the BPM probability distribution of ordinal patterns $P$ and the uniform distribution $U$. We obtain the maximum possible value of $K[P, U]$ when one of the components of $P$ is equal to one, with zero in all other components.

$$K_{\text{max}} = -\frac{1}{2} \left[ \frac{d! + 1}{d!} \log(d! + 1) - 2 \log(2d!) + \log(d!) \right]$$  

The values of the normalized permutation entropy $J_z \in [0,1]$ embraces a large number of possibilities in terms of complexity values, $B_{\text{min}} \leq B \leq B_{\text{max}}$, a standard procedure is implemented to obtain the limits of the $B_{\text{min}}$ and $B_{\text{max}}$ limits defined by ref [28].

Both complexity measure, $J_z$ and $B_z$ represents the cornerstones for the Information Theory. $J_z$ is a powerful complexity measure to evaluate the degree of randomness inherent in a stochastic process. Thus, lower permutation entropy reflects higher predictability due to the tendency to repeat only a few ordinal patterns. In contrast, higher entropy reveals lower predictability due to the tendency to exhibit all possible ordinal patterns.

In this way, for a given permutation entropy value, Jensen–Shannon statistical complexity reflects a measure that an efficient measure used in the analysis of the randomness of the studied system or phenomenon taking into account its physical components (structural correlations) [29]. The definition of statistical complexity [27] ensures that both strictly increasing and decreasing series (for which $J[P] = 0$) and completely random series (for which $K[P, U] = 0$) have zero complexity.

Specifically, considering the intermediate entropy values, which differ from zero it is possible to observe the highest structural complexity. In this case, we compute the maximum complexity as the largest difference of the distribution from the uniform distribution. Given this, for a given time series, we quantify simultaneously both the degree of correlational structure and the randomness in the system fluctuations [13].

2.3 Sliding window technique

We applied the sliding window technique to promote a time dependent analysis of $H$ and $F$. The Sliding window technique proceeds as follows. Considering a time series $y_1, \ldots, y_N$, we construct the sliding windows $k_1y_{1+t\Delta}, \ldots, y_{w+t\Delta}, \ t = 0, 1, \ldots, \left[ \frac{N-w}{\Delta} \right]$. The term $w \leq N$ is the window size, $\Delta \leq w$ is the sliding step, and $\left[ x \right]$ corresponds to taking the integer part of the argument. We use the values inherent of the time series in each window $k_t$ to calculate the Permutation entropy and the Jensen–Shannon statistical complexity, which yield the time evolution of the window position in the CECP.

3. Data

We examine the daily closing price of 26 Chinese sectoral indices. For each Chinese sectoral indices, the periods cover more than 10 years from June 21, 2010, to December 11, 2020. The data were obtained at Standard&Poors.
Fig. 1. The temporal evolution inherent to the times series of the daily closing prices of Chinese sectoral indices from June 21, 2010, to December 11, 2020.
Fig. 2. The trajectory of Chinese sectoral indices from June 21, 2010, to December 11, 2020, in the CECP. The red dots present the random ideal position \((H_i = 1, B_i = 0)\). From an economic perspective, the Chinese sectoral indices that are located more distant \((H_i = 1, B_i = 0)\) are characterized by high entropy and low complexity. Otherwise, the Chinese sectoral indices closer to \((H_i = 1, B_i = 0)\) are defined by more complexity and less entropy.

(https://www.standardandpoors.com/en_US/web/guest/home). Let the data consists of financial time series \(X(t)\), where \(t\) is a discrete variable \(t_i\) with a total of 2713 data points. A list of Chinese sectoral indices considered in this analysis is presented in Table 1.

4. Analysis

The complex dynamics inherent of the fluctuations in financial asset prices affect the personal people around the world [30] and harmful the stability economic and consequently in the welfare state [31].

The study of fluctuations in the financial price assets allows a better understanding of the phenomenology of financial crises [32,33] and the key factors to provide economic stability [34], considering the respective markets: financial, the goods and services market, and the labor.

Because of this, the Bandt & Pompe (BPM) method is a powerful tool for treating time series that are not completely stationary. Past works provides empirical evidences that the Bandt–Pompe permutation entropy discriminates time series. They show that the time series of prices promote more robust results than the time series of returns [17]. The temporal evolution of daily closing prices of 26 Chinese sectoral indices is shown in Fig. 1.

We employed the CECP to map the Chinese sectoral indices and their respective locations are studied along this plane. For each time series of daily closing prices of Chinese sectoral indices, we calculate the Information Theory quantifiers \(H\) and \(C\) considering \(d = 5\) to satisfy the condition \(T > 5d!\).
Fig. 3. For each Chinese sectoral indices the trajectory related to the inefficiency considering the distance of CECP position from the right vertex (1, 0).
Fig. 4. Trajectory in the CECP of Chinese sectoral indices time series for embedding dimension $d = 4$, window size $w = 120$ days and sliding step $\Delta = 20$ days.
We also investigate the behavior dynamics of the shuffled time series of Chinese sectoral indices. Therefore, we used the CECP in these series, where we employ a shuffling procedure with $1000 \times N$ transpositions for each series. Fig. 2 shows the trajectory in the CECP of Chinese sectoral indices from June 21, 2010, to December 11, 2020, for the embedding dimension $d = 5$, and the shuffled series.

We find that Chinese sectoral indices that are located closer to the lower right region of the CECP present high entropy and low complexity. This suggests that their behavior is closer to a random walk (more efficient) [19,21]. Taking into account that the Chinese sectoral indices prices were a pure random walk the variations would be a completely uncorrelated string of numbers and their associated entropy values would be maximized [35,36].

Entropy is a useful tool to Information Theory to estimate the predictability regarding efficiency or inefficiency of the financial market [19,37,38]. Therefore, the more entropy the market has, the higher its efficiency. This is due to the fact that several agents that operate in this market will have little or no information about this asset [17]. This implies an abrupt decrease related to the quantity and quality of disposal information, so there is a natural tendency for a reduction in extreme speculative activities and, consequently, in complex movements in stock asset prices [17].

It is important to mention that the certainty related to this statement can be only proved through an effective statistical test, but related works provide empirical evidence of a strong synergy among arbitrage and price fluctuations [39–43] and to neglect them would be a great mistake.
Otherwise, Chinese sectoral indices located near the central region of the CECP have low entropy and high complexity, which reveals that their behavioral dynamics are more distant from the pattern related to random walking and therefore are more inefficient. Given this, the Chinese sectoral indices price fluctuations are somewhat correlated, it implies that the entropy does not attain its maximal value. Thus, the negative entropy can be considered a measure of predictability, reflecting the market’s inefficiency [17,19,37,38].

The permutation entropy ($H$) and Jensen–Shannon complexity ($C$) are used to evaluate Chinese sectoral indices based on their efficiency. For each Chinese sectoral indices, we show deviations from an ideal position (random walk), evaluating its temporal pattern. From an economic point of view, the higher the distance to this random ideal position the lower its level of efficiency. Table 2 presents the ranking of the Brazilian assets based on the complexity hierarchy ($H \times C$).

Our findings show that TELE, FOOD-DRUG-RET, HOUS-PERI, FOOD-BE-TOB, and CONS-STAP are closer to the lower boundary of the CECP (behavior closer to a random walk). These are the most efficient Chinese sectoral indices [17,19,21,38]. Besides, the Euclidean distance presents a high similarity in the behavior of FOOD-DRUG-RET and HOUS-PERI. It reveals that these Chinese sectoral indices are less complex per entropy value. Otherwise, the Chinese sectoral indices such as MATERIALS, DIV-FINAN, CONS-DISC, IT, and SOFT-SERV are lying distant from the right corner, which implies these indices are less efficient [17] and show long-term correlations.

Then, we investigated the changes suffered in inefficiency by Chinese sectoral indices over time. We apply the CECP analysis in sliding windows (using a size of 120 days with a step of 20 days), and in each window, we calculate the distance of CECP position from the right vertex ($1, 0$), which is our benchmark. We chose the size of the windows described above to obtain a sufficiently long time series for permutation entropy calculations. Fig. 3 presents the inefficiency trajectory, which is constructed using the distance of CECP position from the right vertex ($1, 0$).

Taking into account the period covered in this analysis. We check that the inefficiency index presents a threshold value of 0.2, which segregates the more efficient Chinese sectoral indices from the least efficient ones. The temporal evolution of more inefficient Chinese sectoral indices displays a similar behavior with low fluctuations around this threshold.

For each Chinese sectoral indices, we calculate the impacts of COVID-19 considering the last six years of the daily closing price time series, that is, 5 years before COVID-19 (black graph) and 1 year during COVID-19 (red graph). In the overwhelming majority we have a distinction in behavior between these periods, with increasing market inefficiency during the pandemic period. Fig. 4 shows the trajectory in the CECP of Chinese sectoral indices from June 21, 2010, to December 11, 2020, for embedding dimension $d = 4$, window size $w = 120$ days and sliding step $\Delta = 20$ days.

We investigate the temporal evolution of $H_i$ and $B_i$ considering Pre and Post COVID-19. For both Pre and Post COVID-19, the values of $H_i$ and $B_i$ are show in Fig. 5.

We also present descriptive statistics for log returns. Tables 3 and 4 present the descriptive statistics for the Chinese stock returns for the Pre and Post COVID-19 period. We find that skewness and kurtosis does not seem to change much

\footnote{In order to obtain more accurate statistics we use as a rule of thumb [18] a maximum $d$ obeying $T > 5 t$.}
Table 2
Ranking of the Chinese sectoral indices, values of permutation entropy ($H_S$), Jensen–Shannon complexity ($B_S$) and distance from vertex $(1, 0)$ considering $d = 5$.

| Classify | Assets          | $(H_S)$ | $(B_S)$ | Dist. to $(1, 0)$ |
|----------|-----------------|---------|---------|------------------|
| 1        | TELE            | 0.92513 | 0.11319 | 0.13570          |
| 2        | FOOD_DRUG_RET  | 0.91613 | 0.12513 | 0.15064          |
| 3        | HOUS_PERI       | 0.91185 | 0.12964 | 0.15677          |
| 4        | FOOD_BE_TOB    | 0.90521 | 0.13392 | 0.16407          |
| 5        | CONS_STAP       | 0.90549 | 0.1359  | 0.16553          |
| 6        | LEI             | 0.90283 | 0.13831 | 0.17189          |
| 7        | TECH_HARD       | 0.90215 | 0.14132 | 0.17390          |
| 8        | PHA_BIOT        | 0.89833 | 0.14237 | 0.17495          |
| 9        | FINAN           | 0.89672 | 0.14376 | 0.17701          |
| 10       | HC              | 0.89775 | 0.1455  | 0.17835          |
| 11       | BANKS           | 0.89543 | 0.14591 | 0.17951          |
| 12       | CONS_DURA       | 0.89625 | 0.14801 | 0.18075          |
| 13       | AUTO_COMP       | 0.89683 | 0.1502  | 0.18226          |
| 14       | INSURANCE       | 0.89386 | 0.1513  | 0.18419          |
| 15       | SEMI_COND       | 0.89234 | 0.15076 | 0.18525          |
| 16       | UTILITIES       | 0.89211 | 0.15213 | 0.18650          |
| 17       | TRANSP          | 0.89146 | 0.1523  | 0.18701          |
| 18       | RETAIL          | 0.88828 | 0.15547 | 0.19144          |
| 19       | ENERGY          | 0.88843 | 0.15763 | 0.19314          |
| 20       | CAP_GOODS       | 0.88901 | 0.15868 | 0.19364          |
| 21       | INDUSTRIALS     | 0.88734 | 0.1593  | 0.19516          |
| 22       | MATERIALS       | 0.88464 | 0.15776 | 0.19547          |
| 23       | DIV_FINAN       | 0.88566 | 0.15995 | 0.19661          |
| 24       | CONS_DISC       | 0.87809 | 0.16776 | 0.20732          |
| 25       | IT              | 0.87572 | 0.16873 | 0.20956          |
| 26       | SOFT_SERV       | 0.87637 | 0.16938 | 0.20969          |

Table 3
Descriptive statistics for Chinese stock returns for the pre COVID-19 period. Returns are calculated as $R_t = \frac{p_t - p_{t-1}}{p_{t-1}}$, where $p_t$ is the natural log of the price index ($P_t$), in period $t$.

| Sector     | Mean   | Std. Dev. | Skewness | Kurtosis | Jarque–Bera Probability |
|------------|--------|-----------|----------|----------|--------------------------|
| AUTO_COMP  | 0.0001 | 0.0079    | 0.0725   | 5.2843   | 532.8626                 | 0.00 |
| BANKS      | 0.0000 | 0.0062    | 0.0557   | 6.2565   | 1,079.8550               | 0.00 |
| CAP_GOODS  | 0.0001 | 0.0062    | 0.1615   | 8.4447   | 3,291.2840               | 0.00 |
| CONS_DISC  | 0.0000 | 0.0061    | 0.1551   | 6.5337   | 12,792,840               | 0.00 |
| CONS_DURA  | 0.0000 | 0.0061    | 0.1615   | 8.4447   | 3,291.2840               | 0.00 |
| CONS_STAP  | 0.0000 | 0.0049    | 0.0571   | 6.2565   | 1,079.8550               | 0.00 |
| DIV_FINAN  | 0.0000 | 0.0084    | 0.0607   | 7.6637   | 2,213,6480               | 0.00 |
| ENERGY     | 0.0000 | 0.0066    | 0.0383   | 5.7939   | 794,4899                 | 0.00 |
| FINAN      | 0.0000 | 0.0062    | 0.0058   | 6.1343   | 999,1678                 | 0.00 |
| FOOD_BE_TOB| 0.0000 | 0.0053    | 0.0846   | 6.3559   | 1,148,3730               | 0.00 |
| FOOD_DRUG_RET| 0.0000 | 0.0076    | 0.9723   | 15.3302  | 15,847,7700              | 0.00 |
| HC         | 0.0001 | 0.0058    | 0.05034  | 6.9337   | 1,676,9150               | 0.00 |
| HOUS_PERI  | 0.0002 | 0.0070    | 0.2929   | 7.4613   | 2,059,2340               | 0.00 |
| INDUSTRIALS| 0.0000 | 0.0058    | 0.0511   | 6.8677   | 3,291,2840               | 0.00 |
| INSURANCE  | 0.0000 | 0.0073    | 0.1356   | 5.9779   | 909,4330                 | 0.00 |
| IT         | 0.0002 | 0.0065    | 0.1501   | 5.0410   | 432,8514                 | 0.00 |
| LEI        | 0.0002 | 0.0075    | 0.9811   | 11.3645  | 7,507,6900               | 0.00 |
| MATERIALS  | 0.0001 | 0.0071    | 0.0221   | 7.7529   | 2,297,8180               | 0.00 |
| PHA_BIOT   | 0.0002 | 0.0065    | 1.0813   | 14.1761  | 13,179,500               | 0.00 |
| RETAIL     | 0.0000 | 0.0077    | 0.0016   | 5.5735   | 673,5790                 | 0.00 |
| SEMI_COND  | 0.0002 | 0.0114    | 9.5113   | 251,9584 | 6,340,7180000             | 0.00 |
| SOFT_SERV  | 0.0003 | 0.0069    | 0.0762   | 4.9771   | 399,9234                 | 0.00 |
| TECH_HARD  | 0.0000 | 0.0071    | 0.2999   | 6.0409   | 972,0850                 | 0.00 |
| TELE       | 0.0000 | 0.0052    | 0.1356   | 5.9779   | 909,4330                 | 0.00 |
| TRANSP     | 0.0000 | 0.0058    | 0.0382   | 6.5342   | 1,270,9600               | 0.00 |
| UTILITIES  | 0.0001 | 0.0053    | 0.0413   | 6.1085   | 983,4522                 | 0.00 |

for most economic sectors. An exception would be the semi-conductors sector, which has a large negative skewness and high kurtosis before the COVID-19.

We apply the Jarque–Bera normality test for all economic sectors before and after the crisis. Based on our findings, we can reject the null hypothesis that indices stock returns are normally distributed in almost all cases. Only for the transportation sector, we reject the normality at the 5% significance level for the period after the crisis. For all other economic sectors, we reject this hypothesis using a 1% significance level.
Table 4
Descriptive statistics for Chinese stock returns for the post COVID-19 period. Returns are calculated as $R_t = p_t - p_{t-1}$, where $p_t$ is the natural log of the price index ($P_t$), in period $t$.

| Sector      | Mean  | Std. Dev. | Skewness | Kurtosis | Jarque–Bera p-value |
|-------------|-------|-----------|----------|----------|---------------------|
| AUTO_COMP   | 0.0014| 0.0108    | 0.4980   | 5.0846   | 60.2708             |
| BANKS       | −0.0001| 0.0060   | −0.0030  | 5.7505   | 85.4228             |
| CAP_GOODS   | 0.0002| 0.0062    | −0.0030  | 5.1521   | 64.5168             |
| CONS_DISC   | 0.0007| 0.0084    | −0.3965  | 4.6446   | 37.6406             |
| CONS_DURA   | 0.0005| 0.0085    | −0.4126  | 3.9753   | 18.4277             |
| CONS_STAP   | 0.0006| 0.0063    | −0.3340  | 4.5766   | 33.1063             |
| DIV_FINAN   | 0.0012| 0.0089    | 0.5861   | 8.6513   | 402.9554            |
| ENERGY      | −0.0004| 0.0086  | −0.2408  | 6.7062   | 157.7178            |
| FINAN       | −0.0001| 0.0063   | 0.4947   | 6.1607   | 123.8567            |
| FOOD_BE_TOB| 0.0006| 0.0068    | 0.3118   | 4.5892   | 32.9088             |
| FOOD_DRUG_RET| 0.0002| 0.0074 | −0.1551  | 4.7890   | 37.2273             |
| HC          | 0.0004| 0.0069    | −0.8587  | 4.8843   | 73.3910             |
| HOUS_PERI   | 0.0002| 0.0073    | 0.3951   | 4.2647   | 25.1093             |
| INDUSTRIALS | 0.0002| 0.0056    | −0.3262  | 4.6759   | 36.6108             |
| INSURANCE   | −0.0000| 0.0073  | 0.4852   | 6.2546   | 130.2397            |
| IT          | 0.0009| 0.0091    | −0.7445  | 5.3425   | 86.9993             |
| LEI         | 0.0004| 0.0088    | 0.0894   | 4.3388   | 20.6017             |
| MATERIALS   | 0.0004| 0.0069    | 0.1946   | 5.0635   | 49.7882             |
| PHA_BIOT    | 0.0004| 0.0069    | −0.7787  | 4.6680   | 58.8058             |
| RETAIL      | 0.0007| 0.0095    | −0.3558  | 4.7350   | 39.7091             |
| SEMI_COND   | 0.0013| 0.0129    | −0.5535  | 9.3811   | 500.8433            |
| SOFT_SERV   | 0.0010| 0.0089    | −0.5060  | 4.6789   | 46.0193             |
| TECH_HARD   | 0.0008| 0.0093    | −0.5472  | 4.2985   | 32.5631             |
| TELE        | −0.0005| 0.0080 | 1.1374   | 9.6650   | 560.0357            |
| TRANSP      | 0.0001| 0.0057    | −0.3222  | 3.4726   | 7.2125              |
| UTILITIES   | −0.0001| 0.0054  | 0.1215   | 5.6338   | 78.9928             |

Fig. 6 presents the ratio between the standard deviation before and after COVID-19 for each Chinese sectoral index. The results suggest that more than 70% of the indices observed an increase in volatility in post-COVID-19. Only the capital goods, insurance, transportation, food and drug retail, banks, materials, and industrial sectors maintained the volatility (there was no drop, only maintenance at a similar level).

5. Conclusions
We examine the economic impacts of the public health crisis caused by the COVID-19, considering the Chinese sectoral indices. Therefore, we apply the Bandt & Pompe method to quantify $(H_S)$ and $(B_S)$.
We apply $(H_S)$ and $(B_S)$ to build-up the 2D plane $(H_S \times B_S)$, which allows us to evaluate the randomness in time series of daily closing price of 26 Chinese sectoral indices.

Our findings suggest that COVID-19 crisis promotes an increase in the inefficiency in Chinese sectoral indices. However, the crisis’s impacts are not homogeneous across sectors, which indicates that large global shocks change stock markets’ dynamics. Diversification plays a vital role to absorb these shocks, reducing systematic risk.

Declaration of competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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