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Modelling stock market data in China: Crisis and Coronavirus

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ABSTRACT

Global financial markets experienced distinct collapses during the global financial crisis in 2008 and the COVID-19 pandemic in 2020, and similarity in the underlying nature is still a hot topic to be investigated. This paper investigates their degree of persistence in order to detect whether the shocks affecting them have temporary or permanent effects by examining the closing prices of the Shanghai and Shenzhen Composite Indices from 1991 to 2020. The results before the coronavirus indicate large degrees of persistence with shocks having permanent effects, while during the coronavirus the results indicate a mean reversion with shocks having temporary effects.

1. Introduction

Global financial markets have witnessed two major shocks in the course of a decade—the global crisis of 2008 triggered by sub-prime mortgage loans and the COVID-19 pandemic in 2020. While in both crises expressive losses were registered in stock markets worldwide in the course of a few weeks, literature thus far has missed the opportunity for an in-depth analysis of the similarities and dissimilarities caused by both phenomena in stock market time series (Ji et al., 2020; Zhang et al., 2020).

Broadly speaking, time series can be analyzed under distinct components such as trend, seasonality, economic cycles, and economic shocks as captured by persistence and breaks. The longer the time horizon, the more likely accurate conclusions can be drawn to the significance of these components. With this respect, time series from two major Chinese stock markets, Shanghai and Shenzhen, present the desirable characteristics for conducting this case analysis: a length of over 30 years, definite increasing trend over the course of time inherent to the dynamism of Chinese economy, and global relevance as regards to connectivity with other worldwide stock markets.

In this study, the statistical test developed by Robinson (1994) within the ambit of fractional integration techniques is used to assess the long-term memory properties of these two distinct shocks on the stock markets of Shanghai and Shenzhen. To the best of our
knowledge, no previous studies have addressed this literature gap. While the entire analysis was made from the period of 1990 to 2020, the original time series was also split into four subsamples referring to the periods: (i) before the global economic crisis (from 19-Dec-1990 to 13-Feb-2007 for the Shanghai stock market and from 3-Apr-1990 to 13-Feb-2007 for the Shenzhen stock market); (ii) during the global economic crisis (from 13-Feb-2007 to 15-Jul-2010 for both); (iii) before the beginning of COVID-19 pandemic (from 19-Dec-1990 to 30-Dec-2019 for the Shanghai stock market and from 3-Apr-1990 to 30-Dec-2019 for the Shenzhen stock market), and during the COVID-19 pandemic (from 30-Dec-2019 to 20-Apr-2020 for both stock markets).

The mathematical framework is explained in the following sections to determine the differencing parameter and its confidence interval, which are two major issues when analyzing long-term memory properties of random shocks. From an economic perspective, long-memory or long range dependence means that the information from “today” is not immediately absorbed by the prices in the market and investors react with delay to any such information. Depending on the interval, the parameter can infer fundamental characteristics of time series behavior: stationarity, non-stationarity, mean-reverting behavior, and the effects of the shocks.

2. Background on Time Series Analysis

Numerous models have been developed in time series analysis in order to catch the dynamics of the series. The most well-known models are the Auto-Regressive Moving Average, or ARMA(p, q), because they allow a regression to be made upon the previous p times through the linear autoregressive component AR(p) and the filtering of errors coming from the previous q times through the MA(q) component (see Brockwell and Davis, 1991). Furthermore, these models are particularly malleable and many developments have been made to accommodate the structure of the models to the analysis of the time series for better forecasting or to better catch the dynamics of the time series (e.g. Liu and Shi, 2013; Swider and Weber, 2007). However, ARMA cannot represent time series where the correlation between widely spaced times is non-negligible (i.e. long-memory). The parsimony principle imposes that the choice of the ARMA coefficients number cannot be completely free (Stoica and Soderstrom, 1982; Box et al., 2015).

In order to overcome this, the ARMA structure was extended by adding the Fractional Integration component of order d, becoming ARFIMA (p, d, q) (see Granger, 1980, 1981; Granger and Joyeux, 1981; Hosking, 1981). In contrast to the coefficients p and q that are natural numbers, the differencing parameter d is a real number and a statistical procedure is needed to reach a reliable estimate.

A number of empirical studies on the presence of the long-memory in stock market returns have employed ARFIMA models in their analysis. Starting with the pioneering work of Hurst (1951) and Greene and Fielitz (1977), Aydogan and Booth (1988) tested for long-memory using the rescaled range. Fama and French (1988), Porterba and Summers (1988), Diebold and Rudebusch (1989, 1991a, 1991b), and Lo (1991) used a modified rescaled range (R/S) statistic to test for the evidence of long-memory in a sample of US stock returns. With respect to studies that have been carried out on emerging markets, examples can be found in Assaf and Cavalcante (2005), Bellalah et al. (2005), Kilic (2004), and Wright (2002) who applied a FIGARCH model to test long-run dependency in the volatility of, respectively, Egypt, Brazil, Kuwait, Tunisia, and Turkey. Vougas (2004) employed the ARFIMA-GARCH model to Greek stock markets. Several other studies attempt to find nonlinear and/or chaos behavior in market dynamics. Those are summarized by Barnett and Serletis (2000) and include different stock market indices such as FSTE 100. As regards recent applications in stock markets, the ARFIMA modelling has been used by Panas (2001) on the Athens Stock Exchange. Ikeda (2017) applied complementary measurements of the fractal dimension such as the Hurst rescaled range into other relevant stock indices.

3. Methodology

We used fractional integration methods, but using standard techniques is the usual way to investigate this issue by employing unit root/stationary tests: if a series is stationary I(0), shocks will be transitory, disappearing relatively fast. On the contrary, if the unit root hypothesis cannot be rejected, the series is nonstationary I(1), and shocks will have a permanent nature, requiring strong policy actions to recover the original trends. In the context of fractional integration, however, or I(d), the differencing parameter d can be a fraction between 0 or 1, or even above 1, allowing for a much richer degree of flexibility in the dynamic specification of the data. Thus, if d > 0, the series displays long memory, implying that the observations are highly dependent. In this context, if d is smaller than 0.5, the series is still covariance stationary, while d ≥ 0.5 implies non-stationarity. In fact, the series is “more nonstationary” the higher the value of d is in the sense that the variance of the partial sums increase in magnitude with d. If 0.5 ≤ d < 1, the series is nonstationary though mean reverting in the sense that the shocks will disappear by themselves in the long run, contrary to the I(1) case of I(d, d > 1) where shocks will have a permanent nature.

In short, estimating d in a financial time series is relevant because if significantly different from 0 and 0.5, it is related to long memory and to a certain degree of predictability. Additionally, a correct modelling of a time series allows for a more efficient detection of structural breaks. We estimate d by using a frequency domain version of the score statistics of Robinson (1994) which is very appropriate in the context of nonstationary data. Details of this methodology can be found in any of the numerous empirical applications of these tests (Gil-Alana and Robinson, 1997; Gil-Alana and Moreno, 2012; Abbritti et al., 2016).

In the empirical section, we examine a model that includes a constant and a linear time trend where the errors are integrated of order d, that is,

\[ y_t = \alpha + \beta t + x_t, \quad (1 - B)^d x_t = u_t, \quad t = 1, 2, \ldots, \]  

(1)

where B refers to the backshift operator, and \( u_t \) is supposed to be both, uncorrelated and autocorrelated, in the latter case using the exponential spectral model of Bloomfield (1973).
4. Data

We adopt two different indices to reflect the dynamics of the stock market of China. One is the Shanghai Composite Index, which covers all the stocks listed on the Shanghai stock market since July 1991. The other one is the Shenzhen Composite Index, which is calculated based on the entire stocks listed on the Shenzhen stock market and has been issued since April 1991. Meanwhile, there are significant differences for the two Chinese stock markets. More traditional and large firms make up the Shanghai stock, while the Shenzhen stock market tends to include more new emerging and small-medium firms. The data is obtained from WIND (https://www.wind.com.cn) and cross-checked with the data disclosed by the Securities Regulatory Commission. At present, there are 2,224 companies listed on the Shenzhen stock market and 1,511 on the Shanghai stock market.

5. Results

We estimate the model given by equation (1). In all cases we report results based on three different modelling assumptions: 1) with no deterministic terms, i.e., imposing that \( \alpha = \beta = 0 \) a priori in (1); 2) with a constant, i.e., with \( \alpha \) unknown and \( \beta = 0 \) a priori; and 3) allowing for a linear time trend, i.e., with \( \alpha \) and \( \beta \) unknown and freely estimated from the data.

Table 1 focuses on the case of the entire sample size, and the first thing we observe is that the time trend is not required in any single case with the intercept being enough to describe the deterministic part in the two series and for the two types of disturbances. We also observe that the estimates of \( d \) are significantly higher than 1, being 1.05 for the two series with uncorrelated errors and slightly higher under the model of Bloomfield (1973), suggesting the two series display large degrees of persistence with the shocks having permanent effects.

Table 2 focuses data ending at the beginning of the 2007/08 crisis (February 13, 2007). We observe that the results are very similar with estimates of \( d \) higher than 1 in the two series and slightly higher than the results in the previous case (1.06 and 1.05 for Shanghai and Shenzhen with uncorrelated errors and 1.08 and 1.07 with autocorrelation). However, if we focus specifically on the time of that crisis (February 13, 2007 – July 15, 2010), Table 3 shows that the values are substantially smaller and that the I(1) hypothesis, which may be consistent with a weak version of the efficiency market hypothesis, Fama (1970), cannot be rejected now in three out of the four cases presented. Evidence of mean reversion (i.e., \( d < 1 \)) cannot be found in any single case.

Next, we examine the data ending at the time of the outbreak of the COVID-19 pandemic (December 30, 2019). These are displayed in Table 4, and we observe that they are very similar to those reported across Tables 1 and 2 with estimates of \( d \) significantly higher than 1.

Finally, focusing on the period of the coronavirus crisis, the estimates of \( d \) are now significantly smaller as shown in Table 5, especially under the auto-correlated model of Bloomfield (1973). This is interesting since it can give us evidence of mean reversion with shocks having temporary effects. However, we also observe that the confidence intervals are sufficiently wide for the unit root hypothesis not to be rejected. It is a moot point where increasing the number of observations during this pandemic would narrow the confidence interval, thereby supporting the hypothesis of mean reversion.

This implies that the two stock market series examined are highly persistent with orders of integration significantly higher than 1 when using long sample sizes. However, when focusing on the specific periods of the crisis, both the 2007/08 one and the current Pandemic crisis, the orders of integration are substantially smaller and the unit root null hypothesis cannot be rejected. Nevertheless, we could not find significant evidence of mean reversion, though this may be a consequence of the smaller sample sizes used in these cases. Thus, according to our results, the series referring to the Pandemic crisis might be mean reverting with the shock having long lasting effects though disappearing in the long run. These results are consistent with previous works in this field that show that stock market prices are very persistent with orders of integrations equal to or higher than 1 (Cheung and Lai, 1995; Gil-Alana, 2006; Al-Shboul and Anwar, 2016).

6. Conclusions

Stock markets have suffered harsh times all over the world due to COVID-19. Although the pandemic has not yet ended, it is...
interesting to make a preliminary empirical analysis to investigate its negative impact, which will shed light on the effectiveness of bailout plans to ease the shock. The Chinese stock market, including Shanghai and Shenzhen, is one of the biggest stock markets among emerging countries and has been usually ignored in the literature. This paper uses the statistical test developed by Robinson (1994) to identify the most appropriate value of the differencing parameter $d$ and estimate the influence of this unprecedented COVID-19 crisis.

### Table 2
Estimates of $d$ for the sample ending at 13-February-2007.

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 1.02 (1.00, 1.05) | 1.06 (1.04, 1.09) | 1.06 (1.04, 1.09) |
| SHENZHEN | 1.01 (0.98, 1.04) | 1.05 (1.03, 1.08) | 1.05 (1.03, 1.08) |

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 1.03 (0.99, 1.07) | 1.08 (1.04, 1.13) | 1.08 (1.04, 1.13) |
| SHENZHEN | 1.00 (0.97, 1.05) | 1.07 (1.04, 1.11) | 1.07 (1.04, 1.11) |

The selected specification for the deterministic components are in bold. In parenthesis is the 95% confidence band of the non-rejection values of $d$.

### Table 3
Estimates of $d$ for the 2007/08 crisis.

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 1.00 (0.95, 1.05) | 1.01 (0.97, 1.06) | 1.01 (0.97, 1.06) |
| SHENZHEN | 1.00 (0.95, 1.05) | 1.05 (1.01, 1.10) | 1.05 (1.01, 1.10) |

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 0.99 (0.92, 1.09) | 1.04 (0.98, 1.11) | 1.04 (0.98, 1.11) |
| SHENZHEN | 0.99 (0.93, 1.09) | 1.02 (0.97, 1.10) | 1.02 (0.97, 1.10) |

The selected specification for the deterministic components are in bold. In parenthesis is the 95% confidence band of the non-rejection values of $d$.

### Table 4
Estimates of $d$ for the sample ending at 30-December-2019.

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 1.02 (1.00, 1.04) | 1.05 (1.03, 1.07) | 1.05 (1.03, 1.07) |
| SHENZHEN | 1.00 (0.99, 1.03) | 1.05 (1.03, 1.07) | 1.05 (1.03, 1.07) |

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 1.00 (0.99, 1.05) | 1.07 (1.04, 1.10) | 1.07 (1.04, 1.10) |
| SHENZHEN | 1.00 (0.97, 1.03) | 1.06 (1.03, 1.09) | 1.06 (1.03, 1.09) |

The selected specification for the deterministic components are in bold. In parenthesis is the 95% confidence band of the non-rejection values of $d$.

### Table 5
Estimates of $d$ for the COVID-19 crisis.

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 0.95 (0.81, 1.16) | 0.93 (0.78, 1.15) | 0.93 (0.76, 1.15) |
| SHENZHEN | 0.95 (0.81, 1.16) | 0.95 (0.79, 1.17) | 0.95 (0.79, 1.17) |

| Series   | No terms | With a constant | With a time trend |
|----------|----------|-----------------|------------------|
| SHANGHAI | 0.87 (0.62, 1.22) | 0.81 (0.53, 1.29) | 0.80 (0.34, 1.29) |
| SHENZHEN | 0.87 (0.59, 1.22) | 0.85 (0.53, 1.29) | 0.86 (0.52, 1.27) |

The selected specification for the deterministic components are in bold. In parenthesis is the 95% confidence band of the non-rejection values of $d$.
The empirical results show that the estimates of $d$ are significantly smaller during the period of the coronavirus crisis than during other crisis periods before this pandemic, indicating that the Chinese stock market has characteristics of mean reversion with shocks having temporary effects. Furthermore, even if the confidence interval of the COVID-19 period is wider than those of other periods because of the smaller sample, most of its length lies below the value of 1. This signals that a more intense weakening of stock market stability could have taken place with respect to the financial crisis since the probability that $d$ is smaller than 1 is higher than the probability of $d$ being greater than 1. Before this pandemic, even during the global financial crisis that broke out in 2007, the estimated value of parameter $d$ for the Chinese stock market was above 1, suggesting large degrees of persistence with shocks having permanent effects. This may be a consequence of the fact that the spread of COVID-19 had been almost stopped before the end of February 2020 in China. The Chinese government’s rapid and effective response helped restart the economy as well as increase investor confidence.

Future research should also replicate this analysis in other stock markets such as in the US and in Brazil, which are the two countries most affected by the COVID-19 pandemic.

This paper can be extended in various directions. For example, structural breaks can be specifically tested by using some of the methods developed in recent years in the context of fractional integration (Gil-Alana, 2008; Hwang and Shin, 2018; etc.). Non-linear structures can also be considered, producing changes in a less abrupt way than with the structural breaks.

CRediT authorship contribution statement

Lorenzo Cristofaro: Software, Writing - original draft. Luis A. Gil-Alana: Methodology, Supervision, Funding acquisition. Zhongfei Chen: Data curation, Resources, Formal analysis, Writing - original draft. Peter Wanke: Conceptualization, Writing - review & editing.

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