MODELLING FINANCIAL DATA IN CHINA: CRISIS AND CORONAVIRUS

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Abstract:

This paper deals with the analysis of the financial stock market in China, investigating its degree of persistence in order to know if shocks affecting them have temporary or permanent effects. For this purpose we examine the closing prices of the Shanghai and Zhenzhen Composite Indices, with data starting at July and April 1991 respectively and ending at March 2020. Looking at the sample before the coronavirus, the results indicate large degrees of persistence with shocks having permanent effects. Meanwhile, during the period of the coronavirus, the results indicate mean reversion with shocks having temporary effects. This may result from the Chinese government's rapid and effective responses during the outbreak of the pandemic.

JEL Classification: C22; E31; E44; G10

Keywords: Financial stock market; China; long memory; persistence

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1. Introduction

In time series analysis many models have been developed in order to catch the dynamics of the series. The most famous are the ARMA(p, q) models because they allow to make a regression upon the previous p times through the linear autoregressive component AR(p) and filtering the 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 were made to accommodate the models structure to the analysis of the time series for a better forecasting or to catch better the dynamic of the time series (e.g. Liu and Shi, 2013; Swider and Weber, 2007). In any case, ARMA cannot represent time series where the correlation between widely spaced times is non-negligible (i.e. long-memory). The parsimony principle, indeed, imposes that the choice of the ARMA coefficients number cannot be completely free (Stoica and Soderstrom, 1982; Box et al., 2015).

In order to implement this issue, the ARMA structure was extended, adding the Fractional Integration component of order d, gaining 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 get a reliable estimate.

In this study the statistical test developed by Robinson (1994) is used to identify the most appropriate value for the differencing parameter d. In the following section, the mathematical framework is explained to determine the differencing parameter and its confidential interval. Depending on the interval in which it can be, the parameter can infer fundamental characteristics of time series behaviour: stationarity, non-stationarity, mean-reverting behaviour and the effects of the shocks.

In this study, the parameter d is estimated to understand how the economic crisis of 2008 and the shock due to COVID-19 period affected the stock markets of Shanghai and Shenzhen. Besides the analysis made on the whole period from 1990 to 2020, the rest of the time series are obtained by dividing the whole sample into four subsamples referring to the period before the economic crisis (from 19-Dec-1990 to 13-Feb-2007 for Shanghai stock market, and from 3-Apr-1990 to 13-Feb-2007 for Shenzhen stock market), during the crisis (from 13-Feb-2007 to 15-Jul-2010 for both); before the beginning of COVID-19 (from 19-Dec-1990 to 30-Dec-2019 for Shanghai stock market, from 3-Apr-1990 to 30-Dec-2019 for Shenzhen stock market), and during the COVID-19 emergency (from 30-Dec-2019 to 20-Apr-2020).

2. Methodology

We use fractional integration methods. This is a very useful technique if we want to say something about the nature of the shocks. Using standard techniques, the usual way to investigate this issue is to employ 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 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 $d \geq 0.5$ implies nonstationarity, in fact, the series is "more nonstationary" as higher the value of d is, in the sense that the variance of the partial sums increase in magnitude with d); if $0.5 \leq d < 1$, 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.

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 (see, e.g., Gil-Alana and Robinson, 1997; Gil-Alana and Moreno, 2012; Abbritti et al., 2016; etc.).

3. 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 in the Shanghai stock market and has been published since July 1991. The other one is Shenzhen Composite Index, which is calculated based on the whole stocks listed in the Shenzhen stock market and has been issued since April 1991. Meanwhile, there are significant differences for the two Chinese stock markets. There are more traditional and big-size firms in the Shanghai stock, while more new emerging and small-medium-size firms in the Shenzhen stock. The data is obtained from a professional financial information website in China, i.e. WIND (https://www.wind.com.cn). It has been cross checked with the data from a website designated to disclose inform of listed companies by China Securities Regulatory Commission (http://www.cninfo.com.cn). At present, there are 2224 listing companies in the Shenzhen stock market, while 1511 listing ones in the Shanghai stock market.

FIGURE 1 ABOUT HERE

4. Results

We start this section by examining a model that includes a constant and a linear time trend and where the errors are integrated of order d, that is,

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t, \qquad (1 - B)^{d_o} x_t \;=\; u_t, \qquad t \;=\; 1, 2, \ldots, \tag{6}$$

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). 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 α unknown and $\beta = 0$ a priori; and 3) allowing for a linear time trend, i.e., with α and β unknown and freely estimated from the data.

TABLE 1 ABOUT HERE

Table 1 focusses on the case of the whole sample size, and the first thing we observe is that the time trend is not required in any single case, 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). Thus, according to these results, the two series displays large degrees of persistence, with shocks having permanent effects.

TABLES 2 AND 3 ABOUT HERE

Next, in Table 2 we focus on 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 in the previous case (1.06 and 1.05 for Shanghai and Shezhen 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), in Table 3, the values are substantially smaller, and the I(1) hypothesis (which may be consistent with a weak version of the efficiency market hypothesis, Fama (1970)) cannot be now rejected 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 explosion of the coronavirus and the COVID-19 pandemic (December 30, 2019). They 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.

TABLES 4 AND 5 ABOVE HERE

Finally, focussing on the period of the coronavirus crisis, the estimates of d are now significantly smaller, especially under the autocorrelated model of Bloomfield (1973). This is interesting since it can show us evidence of mean reversion with shocks having temporary effects. However, we also observe that the confidence intervals are wide enough such that the unit root hypothesis cannot be rejected. It is an open question to know if increasing the number of observation during this pandemic, the confidence interval will narrow supporting then the hypothesis of mean reversion.

5. Conclusions

Due to the COVID-19, the stock market has experienced harsh times across the whole world. Although the pandemic has not yet been ended, it is interesting to make preliminary empirical analysis to investigate its negative impact, which will shed lights on the bailout plan to ease the shock. The Chinese stock market, including Shanghai and Shenzhen Stock, is one of the biggest stock market in the 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 pandemic COVID-19.

The empirical results show that the estimates of d are significantly smaller during the period of the coronavirus crisis than during other periods of crisis 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 the ones of the other periods because of the smaller sample, most of its length lies below the value of 1. This highlights that a strongest weakening of the stock markets stability could have happened respect to the financial crisis, as the probability that d is smaller than 1 is higher than the probability that d is greater than 1. Before this pandemic, indeed, even during the global financial crisis broke out since 2007, the estimated value of the parameter d for the Chinese stock market has been above 1 evidently, suggesting large degrees of persistence, with shocks having permanent effects. This may be a consequence of the fact that the spread of the COVID-19 has been almost stopped before the end of February of 2020 in China. The Chinese government's rapid and effective responses help to restart of economy as well as increase the investors' confidence. This finding still need to be confirmed when obtaining more observations, especially when the pandemic is finally ended.

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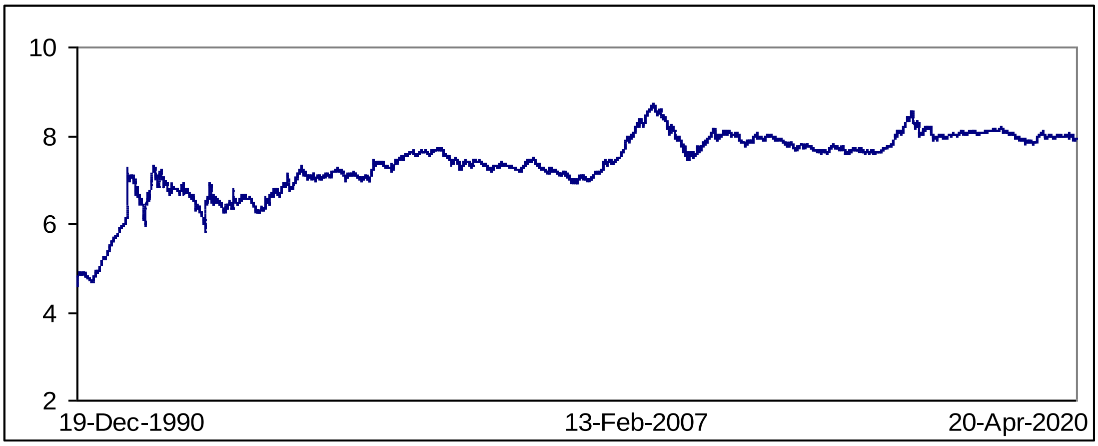
Tables and Figures

Figure 1: Time series plots

SHANGHAI



SHENZHEN

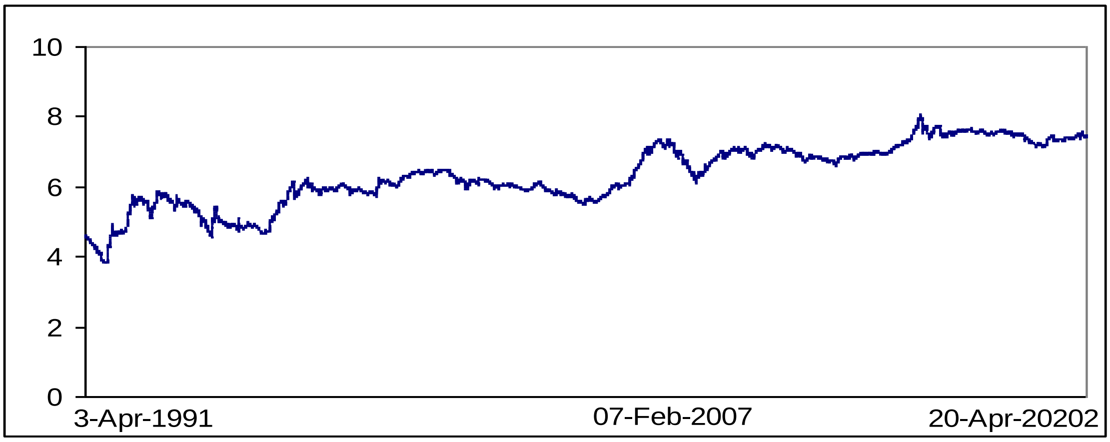


Table 1: Estimates of d for the whole sample

i) No autocorrelation			
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	1.01 (0.99, 1.03)	**1.05 (1.03, 1.07)**	1.05 (1.03, 1.07)
i) With autocorrelation			
Series	No terms	With a constant	With a time trend
SHANGHAI	1.04 (1.01, 1.05)	**1.07 (1.04, 1.10)**	1.07 (1.04, 1.10)
SHENZHEN	1.01 (0.97, 1.03)	**1.06 (1.03, 1.09)**	1.06 (1.03, 1.09)

In bold the selected specification for the deterministic components. In parenthesis, the 95% confidence bands of the non-rejection values of d.

Table 2: Estimates of d for the sample ending at 13-February-2007

i) No autocorrelation			
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)
i) With autocorrelation			
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)

In bold the selected specification for the deterministic components. In parenthesis, the 95% confidence bands of the non-rejection values of d.

Table 3: Estimates of d for the 2007/08 crisis

i) No autocorrelation			
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)
i) With autocorrelation			
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)

In bold the selected specification for the deterministic components. In parenthesis, the 95% confidence bands of the non-rejection values of d.

Table 4: Estimates of d for the sample ending at 30-December-2019

i) No autocorrelation			
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)
i) With autocorrelation			
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)

In bold the selected specification for the deterministic components. In parenthesis, the 95% confidence bands of the non-rejection values of d.

Table 5: Estimates of d for the COVID-19 crisis

i) No autocorrelation			
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)
i) With autocorrelation			
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)

In bold the selected specification for the deterministic components. In parenthesis, the 95% confidence bands of the non-rejection values of d.