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Cross-correlations between Renminbi and four major currencies in the Renminbi currency basket

Gang-Jin Wang [a], Chi Xie [a,b,*]

[a] College of Business Administration, Hunan University, Changsha 410082, China

[b] Center of Finance and Investment Management, Hunan University, Changsha 410082, China

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ABSTRACT

We investigate the cross-correlations between Renminbi (CNY) and four major currencies (USD, EUR, JPY, and KRW) in the Renminbi currency basket, i.e., the cross-correlations of CNY–USD, CNY–EUR, CNY–JPY, and CNY–KRW. *Qualitatively*, using a statistical test in analogy to the Ljung-Box test, we find that cross-correlations significantly exist in CNY–USD, CNY–EUR, CNY–JPY, and CNY–KRW. *Quantitatively*, employing the detrended cross-correlation analysis (DCCA) method, we find that the cross-correlations of CNY–USD, CNY–EUR, CNY–JPY, and CNY–KRW are weakly persistent. We use the DCCA cross-correlation coefficient ρ_{DCCA} to quantify the level of cross-correlations and find the currency weight in the Renminbi currency basket is arranged in the order of USD $>$ EUR $>$ JPY $>$ KRW. Using the method of rolling windows, which can capture the time-varying cross-correlation scaling exponents, we find that: (i) CNY and USD are positively cross-correlated over time, but the cross-correlations of CNY–USD are anti-persistent during the US sub-prime crisis and the European debt crisis. (ii) The cross-correlation scaling exponents of CNY-EUR have the cyclical fluctuation with a nearly two-year cycle. (iii) CNY–JPY has long-term negative cross-correlations, during the European debt crisis, but CNY and KRW are positively cross-correlated.

1. Introduction

The Renminbi (RMB), verbatim translated as "the people's currency", is the currency of China. RMB is also known as the Chinese Yuan (CNY), and its currency symbol is denoted as "¥". Recently, there have been two major events in the RMB exchange rate: (i) On July 21, 2005, after a decade-long of pegging RMB to US dollar (USD), the People's Bank of China (PBoC, i.e., the China's central bank) announced that the RMB exchange rate would become "*adjustable, based on market supply and demand with reference to exchange rate movements of currencies in a basket*" [1,2]. Then, the governor of China's central bank, Xiaochuan Zhou, revealed details of the RMB currency basket that "*dominant amongst a raft of currencies are USD, the euro (EUR), the Japanese yen (JPY) and South Korea's won (KRW)*". (ii) Actually, during the US sub-prime crisis, RMB was re-pegged to USD. On June 19, 2010, PBoC announced that, it has "*decided to proceed further with reform of the RMB exchange rate regime and to enhance the RMB exchange rate flexibility*" [3]. Along with the rapid economic growth of China, the RMB exchange rate (or RMB currency basket) has spurred a large amount of attention in academic and industrial circles, even in the political arena [4].

Financial markets are considered as complex dynamic systems with a great number of interacting agents [5–7]. The foreign exchange markets, which represent the largest and most liquid financial market in the world, are extremely

* Corresponding author at: College of Business Administration, Hunan University, Changsha 410082, China. Tel.: +86 731 88823890; fax: +86 731 88823670.

E-mail address: xiechi@hnu.edu.cn (C. Xie).

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important [8]. One of the considerable characteristics of market dynamics is the presence of cross-correlations between financial variables [9]. Hence, in this study, we seek to investigate the cross-correlations between RMB and the major currencies in the RMB currency basket.

In previous studies, many different approaches have been proposed to quantify the cross-correlations between financial entries, such as various clustering methods [8,10–12], the random matrix theory [13,14], and the cross-sample entropy [15,16]. A common assumption of the above-stated methods is that both of the analyzed time series are stationary. However, in the real-world, the financial time series are usually heterogeneous and nonstationary [17]. To overcome this limitation, many methods are developed to examine the auto-correlation and cross-correlation using the mono- and multifractal theory in various fields. For a noisy and nonstationary time series, Peng et al. [18] proposed the detrended fluctuation analysis (DFA) method to study the fractal structure of the DNA nucleotides sequence. After that, DFA was widely used to determine long-range dependence and auto-correlation of the nonstationary time series [19–26]. Vandewalle and Ausloos [27] devised an alternative approach of DFA, which is termed as the detrending moving average (DMA) algorithm, to investigate the long-range correlations of nonstationary time series. Based on DFA, Podobnik and Stanley [28] proposed the detrended cross-correlation analysis (DCCA) to quantify power-law cross-correlations between simultaneously recorded nonstationary time series. Then, DCCA becomes a versatile and powerful method to investigate the cross-correlations between the financial variables [9,29–31]. For instance, Podobnik et al. [29] analyzed 14, 981 daily data of the Standard and Poor's 500 Index in the period between 1950–2009, and found power-law cross-correlations between volume change and price change by means of DCCA. Based on DCCA, Siqueira et al. [9] examined 1, 908 daily observations of different stocks and commodities on the Brazilian market from August 10, 2000 to April 30, 2008, and found strong cross-correlations of the volatility time series in the Brazilian stock and commodity market. Lin et al. [30] analyzed the cross-correlations behavior in US and Chinese stock markets using DCCA. Their results showed that cross-correlations in Chinese stock markets (i.e., Shanghai stock market and Shenzhen stock market) are stronger than that of between US and Chinese stock markets. Recently, Zebende [32] proposed a new detrended cross-correlation coefficient (i.e., DCCA cross-correlation coefficient, ρ_{DCCA}), which was defined in terms of DFA and DCCA, to quantify the level of cross-correlation between nonstationary time series. Vassoler and Zebende [33] applied the coefficient ρ_{DCCA} to analyze and quantify cross-correlations between air temperature and air relative humidity. Podobnik et al. [34] examined the statistical significance of the coefficient ρ_{DCCA}, and proposed an additional statistical test to quantify the cross-correlations between two power-law correlated time series.

In this paper, we examine the cross-correlations between RMB (CNY) and four major currencies (i.e., USD, EUR, JPY, and KRW) in the RMB currency basket. We first make a preliminary analysis of the 5 currencies (CNY, USD, EUR, JPY, and KRW) from July 21, 2005 to May 25, 2012. Next, we qualitatively analyze the cross-correlations using the cross-correlation statistics proposed by Podobnik et al. [35]. Then, we employ DCCA and DCCA cross-correlation coefficient ρ_{DCCA} to study the presence of cross-correlations quantitatively. Finally, we use the method of rolling windows to capture the dynamics of the cross-correlations.

The remainder of this paper is organized as follows. In the next section, we provide the methodologies of DCCA and DCCA cross-correlation coefficient ρ_{DCCA}. In Section 3, we present the data set and make a preliminary analysis. We show the main empirical results and some relevant discussions in Section 4. Finally, in Section 5 we draw some conclusions.

2. Methodology

2.1. Detrended cross-correlation analysis

Detrended cross-correlation analysis (DCCA) is used to investigate the cross-correlations between two nonstationary time series, which can be described as follows [28,30]:

Step 1. Consider two time series $\{x(t)\}$ and $\{y(t)\}$ of the same length N, where $t = 1, 2, \ldots, N$. We can determine the profile as two new series,

$$X(t) = \sum_{i=1}^{t} \left(x(i) - \langle x \rangle\right), \qquad Y(t) = \sum_{i=1}^{t} \left(y(i) - \langle y \rangle\right), \quad t = 1, 2, \ldots, N. \tag{1}$$

Step 2. Both of the profiles $\{X(t)\}$ and $\{Y(t)\}$ are divided into $N_s = \text{int}(N/s)$ non-overlapping segments of equal length s. In this study, we set $10 \le s \le N/4$.

Step 3. For each non-overlapping segment v $(1 \le v \le N_s)$, the local trending functions of $\{X_v(t)\}$ and $\{Y_v(t)\}$ are calculated as $\{\tilde{X}_v(t)\}$ and $\{\tilde{Y}_v(t)\}$ by a least-square fit of the data, respectively.

Step 4. The cross-correlation fluctuation variance for each segment is calculated as follows [17]:

$$F_v^2(s) = \frac{1}{s} \sum_{t=1}^{s} \left| X_v(t) - \tilde{X}_v(t) \right| \left| Y_v(t) - \tilde{Y}_v(t) \right|. \tag{2}$$

Then we average over all segments to obtain the cross-correlation fluctuation function:

$$F_{\text{DCCA}}(s) = \left\{ \frac{1}{N_s} \sum_{v=1}^{N_s} F_v^2(s) \right\}^{1/2}. \tag{3}$$