The Stock Price Of China And The Exchange Rate: A Quantile Autoregressive Distributed Lag Model

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Abstract: This paper uses an innovative method through combining autoregressive distributed lag model and a quantile regression, called a quantile autoregressive distributed lag model, to examine the dynamic long-run equilibrium and short-run causal relationship between the stock price of China and the RMB/USD exchange rate from January 1994 to June 2016. T he results indicate that there is long-run cointegration relationship between the stock price of China and the RMB/USD exchange rates at lower and higher distributions of exchange rates. The causality results show that there is unidirectional causality running from the RMB/USD exchange rate to China stock price at lower and higher distributions of stock prices. The result shows that there is evidence in favor of the goods market hypothesis in China.

Key-words: Exchange rates, Stock prices, Autoregressive distributed lag model, A quantile regression, China, Cointegation

1 Introduction

Over two decades, market participants, researchers, and governments have been concerned the issue of the relationship between exchange rates and stock price. There are two main approaches to examine this relationship. One is the goods market approach which claims that the depreciation of domestic currency affects firm's values through changing in price competitiveness, thereby affecting firm's profits and their stock prices. The other is the portfolio approach which asserts that an increase in stock prices induces a rise in investor's wealth, leading to an increase in the inflows of foreign capital and thereby causing an appreciation in domestic currency.

In the international finance and investment empirical literature, there also exist four findings regarding the causal relationship between exchange rates and stock prices. First, exchange rates Granger cause stock prices (goods market hypothesis), such as Hatemi-J and Roca [7], and Tian and Ma [25]. Second, stock prices Granger cause exchange rates (portfolio hypothesis). This view has been supported by Phylaktis and Ravazzolo [23], Tsai [26], and Hsu [9]. The third finding implies that both exchange rates and stock prices Granger cause each other (feedback hypothesis). This view has been supported by Mok [17] and Ibrahim [10]. Lastly, there is no causality between exchange rates and stock prices (neutrality hypothesis). This hypothesis has been supported by Ajayi, Friedman, and Mehdian [1] and Granger, Huang, and Yang [5]. Furthermore, we surveyed the empirical literatures regarding the causal relationship between exchange rates and stock prices in China. Nieh and Yau [18], Zhao [27], Liu and Wan [16], and Ho and Huang [8] supported neutrality hypothesis; Tian and Ma [25], Liu and Wan [16], Cao [2], Guo, Hu and Jiang [6], Ho and Huang [8], and Sui and Sun [24] supported goods market hypothesis, but Chkili and Nguyen [3] supported portfolio hypothesis.

Based on these China's findings, the past empirical literature is still inconclusive regarding the causal relationship between exchange rates and stock prices in China. Moreover, most of these empirical studies use ordinary least square (OLS) regression and Granger causality test to estimate the impact of the independent variable on t he mean of the conditional dependent variable distribution, which only considers its conditional mean. It cannot describe the dynamic relationship between the independent variable and the dependent variable. The methodology in this study, however, is derived from Hsu's [9] study. We use an innovative regression (called a q uantile autoregressive distributed lag model, QARDL), combining Pesaran, Shin, and Smith [22] developed the bounds test procedure which based on the Auto-Regressive Distributed Lag (ARDL) model, and Koenker and Bassett [13] proposed a quantile regression, to investigate the long-run equilibrium relationship between stock prices and exchange rates, the short-run causal impact of exchange rates on stock prices across different conditional stock price distribution, and the short-run causal impact of stock prices on exchange rates across different conditional exchange rate distribution. Pesaran, Shin, and Smith's [22] ARDL method is more efficient since it does not require a pre-test for co-integration among variables and more robust to conduct long-run equilibrium test. Furthermore, the advantage of using a quantile regression is that a quantile regression will be more robust [15] because it estimates the median and the full range of other conditions, rather than ordinary least squares regression to estimate mean. This paper is organized as follows. In section II, we present the methodology. Section III describes data collection and empirical results. Section IV provides conclusions.

2 Methodology

2.1 Auto-Regressive Distributed Lag Model

Several Pesaran's empirical studies [19, 20, 21, and 22] have indicated that the Auto-Regressive Distributed Lag (ARDL) approach for co-integration is preferable to other conventional co-integration approaches, such as Engle and Granger [4], Johansen [11], and Johansen and Juselius [12] procedures. One of the reasons for using the ARDL is that it has advantage of avoiding the classification of variables into I(1) or I(0) and no need for unit root pre-testing. Another reason for using the ARDL approach is that it is more robust and performs better for small sample sizes than other co-integration techniques. The third reason for preferring the ARDL approach is that it allows that the variables may have different optimal lags and employs a single reduced form equation to estimate the long-run and short-run relationship. Taking each of the variables in turn as a dependent variable in this study, we estimate the following Unrestricted Error Correction model (UECM) based on Pesaran, Shin, and Smith [22] ARDL model:

$$\Delta \ln EXCH_t=\alpha_0+\alpha_1 \ln EXCH_{t-1}+\alpha_2 \ln CHSI_{t-1}+\sum\alpha_{1i}\Delta \ln EXCH_{t-i}+\sum\alpha_{2i}\Delta \ln CHSI_{t-i}+\varepsilon_{1t} \quad (1)$$

$$\Delta \ln CHSI_t=\beta_0+\beta_1 \ln EXCH_{t-1}+\beta_2 \ln CHSI_{t-1}+\sum\beta_{1i}\Delta \ln EXCH_{t-i}+\sum\beta_{2i}\Delta \ln CHSI_{t-i}+\varepsilon_{2t} \quad (2)$$

Here, lnEXCHt is the log of exchange rates which measures the price of USD in terms of the China Renminbi (RMB) and lnCHSIt is the natural log of the Shanghai A Share Index. The sign of Δ is the first difference operator. In order to investigate the long-run relationship between the stock price of China and the RMB/USD exchange rate, this study uses the F-test statistic to test the joint significance of the coefficients on one-period lagged levels of the variables in Equation (1), denoted by $F(EXCH_t|CHSI_t)$, that is, the null hypothesis H_0: $\alpha_1=\alpha_2=0$ against the alternative H_1: $\alpha_1\neq\alpha_2\neq 0$. Similarly, the null hypothesis for testing the non-existence of a long-run relationship in Equation (2) is denoted as $F(CHSI_t|EXCH_t)$. Pesaran [19] and Pesaran, Shin, and Smith [22] provide critical values are based on large sample sizes. The bounds test procedure is applicable regardless of whether or not the underlying regressors are integrated on the order of one or zero, or mutually co-integrated. Furthermore, the ARDL regression yields a test statistic that can be used to compare two asymptotic critical values. If the test statistic lies above the upper bound of critical values, the null hypothesis of a no long-run relationship is rejected whether or not the underlying orders of integration of the regressors are zero or one. Alternatively, if the test statistic is below the lower bound of critical values, the null hypothesis of a no long-run relationship among the regressors cannot be rejected. When the test statistic lies between these two bounds, the results are inconclusive.

Moreover, causality implies that lnCHSI 'Granger-causes' lnEXCH provided that $\alpha_{2i}\neq 0$ for all i in Equation (1). Similarly, in Equation (2), causality implies that lnEXCH 'Granger-causes' lnCHSI provided $\beta_{1i}\neq 0$ for all i.

2.2 A Quantile Regression

A quantile regression is to estimate and conduct inference about conditional quantile function. Koenker and Bassett [13] proposed the quantile regression approach as an alternative to least squares regression in a wide range of applications. This approach takes into consideration the skewness of the distribution and gives a more complete picture of the performance, which is affected by the various independent variables. This technique was further developed by Koenker and Hallock [14] and Koenker [15].

According to Koenker [15], a quantile regression can be used when an estimate of the various quantile of a population is desired. One advantage of using a quantile regression to estimate the median and the full range of other conditions, rather than ordinary least squares regression to estimate mean, is that a quantile regression will be more robust in response to large outliers. Like the least absolute deviations, the quantile regression objective function is a weighted sum of absolute deviations, which gives a robust measure of location, therefore, the estimated coefficient vector is not sensitive to outlier observations on the dependent variable. Furthermore, it also provides a more efficient approach than the least square method when the error term is non-normal.

A quantile regression can be seen as a natural analogue in regression analysis to the practice of using different measures of central tendency and statistical dispersion to obtain a more comprehensive and robust analysis. Another advantage to a quantile regression is the fact that any quantile can be estimated.

According to Koenker and Bassett [13] method, we let $\{ y_t, t = 1,2...,T \}$ be a random sample on the regression process $y_t = u_t + x_t\beta$, having conditional distribution function $F_{Y/X}(y)= F(Y_t \le y)=F(y_t - x_t\beta)$, where $\{ x_t, t = 1,2...,T \}$ denote a sequence of (row) k-vectors of a known design matrix. The θ^{th} regression quantile, $Q_{Y/X}(\theta)$, $0 < \theta < 1$ is defined as any solution to the minimization problem

$$\min_{\beta}\Big[\ \theta\sum_{\{t : Y_t \ge X_t\beta\}}|y_t - x_t\beta| + (1-\theta)\sum_{\{t : Y_t < X_t\beta\}}|y_t - x_t\beta|\ \Big] \quad (3)$$

The resulting solution to equation 3 is denoted as from which we obtain the θ^{th} conditional quantile $Q_{Y/X}(\theta)= x\beta_\theta$. In this paper y_t or x_t can be the stock prices and the exchange rates.

2.3 A Quantile Auto-Regressive Distributed Lag model

In this study we use a quantile autoregressive distributed lag model (QARDL) through combining Pesaran, Shin, and Smith's [22] Auto-Regressive Distributed Lag (ARDL) model and Koenker and Bassett's [13] quantile regression. This method substitutes equation (3) into equations (1) and (2) that can be described to equations (4) and (5), and provides a useful supplement to the standard constant-parameter regression estimate (only one α or β) for studying all possible parameters (for all quantiles) vary across high dependent variable and low dependent variable. Therefore, it leads to a more dynamic and complete understanding of what might really lie behind the stories of great effect or non-effect for the exchange rate on the stock price or the stock price on the exchange rate.

$$\min_{\alpha}\theta\sum\left|\Delta\text{lnEXCH}_t - \alpha_0 - \alpha_1\text{lnEXCH}_{t-1} - \alpha_2\text{lnCHSI}_{t-1} - \sum\alpha_{1i}\Delta\text{lnEXCH}_{t-i} - \sum\alpha_{2i}\Delta\text{lnCHSI}_{t-i}\right|$$
$$+(1-\theta)\sum\left|\Delta\text{lnEXCH}_t - \alpha_0 - \alpha_1\text{lnEXCH}_{t-1} - \alpha_2\text{lnCHSI}_{t-1} - \sum\alpha_{1i}\Delta\text{lnEXCH}_{t-i} - \sum\alpha_{2i}\Delta\text{lnCHSI}_{t-i}\right|$$
(4)

$$\min_{\beta}\theta\sum\left|\Delta\text{lnCHSI}_t - \beta_0 - \beta_1\text{lnEXCH}_{t-1} - \beta_2\text{lnCHSI}_{t-1} - \sum\beta_{1i}\Delta\text{lnEXCH}_{t-i} - \sum\beta_{2i}\Delta\text{lnCHSI}_{t-i}\right|$$
$$+(1-\theta)\sum\left|\Delta\text{lnCHSI}_t - \beta_0 - \beta_1\text{lnEXCH}_{t-1} - \beta_2\text{lnCHSI}_{t-1} - \sum\beta_{1i}\Delta\text{lnEXCH}_{t-i} - \sum\beta_{2i}\Delta\text{lnCHSI}_{t-i}\right|$$
(5)

If we investigate the long-run equilibrium relationship and short-run causality between exchange rates and stock prices, In Equation (4), equilibrium relationship means that the null hypothesis H_0: $\alpha_1=\alpha_2=0$ is against the alternative H_1: $\alpha_1\neq\alpha_2\neq0$ for all i during different θ^{th} conditional quantiles, and causality implies that lnCHSI 'Granger-causes' lnEXCH provided that $\alpha_{2i} \neq 0$ for all i during different θ^{th} conditional quantiles. Similarly, in Equation (5), equilibrium relationship means that the null hypothesis H_0: $\beta_1=\beta_2=0$ is against the alternative H_1: $\beta_1\neq\beta_2\neq0$ for all i during different θ^{th} conditional quantiles, and causality implies that lnEXCH 'Granger-causes' lnCHSI provided that $\beta_{1i} \neq 0$ for all i during different θ^{th} conditional quantiles.

3 Data And Empirical Results

In this study we use monthly China data that covers the period January 1994-June 2016 for a total of 270 observations. The data on RMB/USD exchange rate and China stock prices are compiled from the database of the Taiwan Economic Journal. The RMB/USD exchange rate is measured as the price of US dollar in terms of China Renminbi China Stock prices are measured as the Shanghai A Share Index. All variables are in logarithmic form.

Before estimating equations (4) and (5), this study uses the Augmented Dickey–Fuller (ADF) unit root test to determine the order of integration of the two variables. Table 1 reports the unit root test results in levels and first differences. The results show that we cannot reject the null hypothesis of the unit root for two variables in levels. Applying the ADF test to the first difference of these two series, we are able to reject the null hypothesis of a unit root at the 1% level or better. Based on the results from the ADF test, it is concluded that these two data series are integrated of order one.

Table 1 Results from the Augmented Dickey–Fuller unit root test

	Level	p-value	First-difference	p-value
lnEXCH	-2.240	0.193	-16.074	0.000*
lnCHSI	-1.773	0.394	-17.037	0.000*

* Denotes significance at the 1% level.

In applying the bounds test, this study first specifies the optimal lag length of the UECM on equations (1) to (2). We employs the Schwarz's Bayesian Information Criterion (SBC) to choose the optimal lag length because the SBC tends to define more parsimonious specifications [21]. The lag order which determined from the SBC is 1. The χ^2_{sc} statistic also indicates that there is no serial correlation in the residual when the lag length is equal to 1.

Next, the bounds tests without trend are conducted to confirm the existence of a dynamic long-run equilibrium relationship between the stock price of China and the RMB/USD exchange rate for all i during different θ^{th} conditional quantiles, and the results showed in Table 2. Due to 270 observations, the critical values from Pesaran [19] and Pesaran, Shin, and Smith [22] will be used in the present study. Clearly, using an innovative method, that is, ARDL with a quantile regression, the results found that there exist long-run relationship between the exchange rate and China stock price at lower(0.1 to 0.4 quantiles) and higher(0.9 quantiles) distributions of the exchange rate for $F(EXCH_t|CHSI_t)$ and there is no long-run relationship between China stock price and the exchange rate at any distribution of China stock price for F(CHSIt|EXCHt) in Table 2.

Table 2 C o-integration test results at different quantiles

Quantile	F(EXCHt|CHSIt) F value	F(CHSIt|EXCHt) F value
0.1	10.057*	1.188
0.2	9.845*	0.010
0.3	12.418*	0.822
0.4	8.007*	0.183
0.5	2.831	0.103
0.6	0.014	0.170
0.7	0.519	0.179
0.8	1.237	0.287
0.9	10.274*	0.327
OLS	9.517*	1.826

Note1: Bounds test for cointegration without trend 95% critical value I(0)=2.45 and I(1)=3.61
* Denotes significance at the 5% level.

We present the Granger causality tests with different quantiles in Table 3. The notation of x ≠>y means that variable x does not Granger-cause variable y. With respect to the causal relationship between the stock price of China and the RMB/USD exchange rate during the period of January 1994-June 2016, we find some noteworthy findings. First, the causal relationship between the exchange rate and China stock price is neutral by using traditional OLS method. Second, through using an innovative method, there is no causality running from China stock prices to the RMB/USD exchange rate at any distribution of exchange rates, but there is unidirectional causality running from the RMB/USD exchange rates to China stock prices, which supported the goods market hypothesis, at lower (0.1 quantile) and higher (0.8 and 0.9 q uantiles) distributions of China stock prices in Table 3.

4 Conclusions

Many empirical literatures have examined the relationship between exchange rates and stock prices in China. This paper, however, adopts an innovative approach (QARDL) through combining the auto-regressive distributed lag (ARDL) model and a quantile regression to examine the long-run and causal relationship between the stock price of China and the RMB/USD exchange rate during the period of January 1994-June 2016. According the traditional OLS method, the results clearly indicate that there is only long-run equilibrium between the stock price of China and the RMB/USD exchange rate, but no short-run causal relationship between them. However, through using ARDL model and a quantile regression, the results show that there is a long-run equilibrium relationship between the exchange rate and China stock price only at the lower and higher distribution of the exchange rate. Moreover, there is unidirectional causality running from the RMB/USD exchange rate to China stock price which supported the goods market hypothesis. These empirical results also provide China's investors and policymakers a better understanding of exchange rates and stock prices nexus, especially formulating international financial policy for China governments.

Table 3 Results from causality tests at different quantiles

Quantile	lnCHSI ≠> lnEXCH		lnEXCH ≠> lnCHSI	
	F value	p-value	F value	p-value
0.1	0.031	0.861	16. 796*	0.000
0.2	1. 117	0.292	3. 359	0.068
0.3	0.266	0.607	1.347	0.247
0.4	0.036	0.849	0.313	0.576
0.5	0.000	0.995	0.054	0.817
0.6	0.000	0.993	0.250	0.618
0.7	0.000	0.996	1.933	0.166
0.8	0.025	0.876	5.872*	0.016
0.9	0.0 20	0.887	11.817*	0.001
OLS	0.983	0.322	0.298	0.586

*Denotes significance at the 5% level.

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