## AMERICAN UNIVERSITY OF BEIRUT

# THE EFFECT OF EXCHANGE RATE ON STOCK PRICES IN CHINA

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A project submitted in partial fulfillment of the requirements for the degree of Master of Arts in Financial Economics to the Department of Economics of the Faculty of Arts and Sciences at the American University of Beirut

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## AMERICAN UNIVERSITY OF BEIRUT

## THE EFFECT OF EXCHANGE RATE ON STOCK PRICES IN CHINA

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## AN ABSTRACT OF THE PROJECT OF

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This study examines the effect of exchange rate on stock market in China. We employ daily data on SSE composite index as proxy for Shanghai stock exchange and on USD/CNY exchange rate for the 10 years period between January 1, 2009 and January 1, 2019 (post 2008 financial crisis period) in an unrestricted VAR model. After conducting cointegration test, Granger causality test, orthogonal variance decomposition and impulse response function, we find that there's no long run relation between exchange rate and stock prices in China, whereas exchange rate appreciation is found to have a negative but minimal effect on Chinese stock prices in the short run.

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## CHAPTER 1 INTRODUCTION

China experienced a tremendous GDP growth rate for 30 years. Measured by purchasing power parity (PPP) China was declared by the central intelligence agency the largest economy in 2017. The European union follows in the second place, and the United States in the third place. Together, these three largest economies produced fifty percent of the world's total output. China alone contributed to nineteen percent of the world's total GDP with a total output of \$23 trillion (CIA, 2017). This enormous growth is attributed to its mixed type of economy which combines command economy with limited capitalism, with government spending being the main driver of the Chinese GDP growth. Moreover, the controlled exchange rate by the central bank, the people's Bank of China, offers China an international trade advantage. The central bank, by maintaining the USD to Yuan exchange rate at high price leads to relatively cheaper exporting goods comparing with other country's goods. This strategy increases the Chinese exports which subsequently boosts the Chinese gross domestic product. Nonetheless, the massive government expenditures along with corporate and personal debts over the years resulted in a 260% debt-to-GDP ratio. In addition, overborrowing driven by low interest rate created asset bubble and inflation (Bloomberg, 2017). The low interest rate also shrank the returns on saving accounts which decreased consumers' wealth, leading to low domestic consumption. These factors significantly slowed down the rate GDP's growth.

To prevent economic crisis, the Chinese authorities have considered a long-term plan for economic reform, announced by the President Xi Jinping on November 16, 2013, which consists of a shift from the dependency on high government spending and low-cost exports towards more domestic consumption and private investment. However, the GDP growth rate dropped more after the economic reform. China has been facing a decreasing growth rate since 2013, after benefiting of a double-digit growth rate for decades. Reported by IMF, the GDP year-on-year change in China decreased from 7.8% in 2013 to 7.3% in 2014, to 6.9% in 2015, and to 6.7% in 2016, reaching a rate of 6.6% in 2018. In addition, the economic slowdown in China has affected many big international companies, according to CNN. China's fear concerning expected deterioration in standard of living subsequent to the decline in GDP growth rate highlights need for new rescuing strategies. The Chinese authorities find a way out from this dilemma by encouraging investment in the stock market in an attempt to increase wealth and boost growth. Moreover, selling stocks works as an alternative to banks debt as funding strategy for corporations. Stock markets may be affected by macroeconomics variables, one of these variables is the exchange rate.

Historically the Chinese Yuan was pegged to the U.S Dollar by the central bank of China. The PBOC used to intervene in foreign exchange market to keep the Chinese Yuan to U.S dollar exchange rate relatively high which gave China trade advantage over the United States. After long periods of international pressure, especially by the United States, on China to move towards flexible exchange rate, the Chinese authorities announced a reform of the exchange rate regime in July 2005 which addresses a switch from fixed to floating exchange. The exchange rate has been relaxed but remained carefully managed. According to IMF, the USD to Yuan exchange rate has depreciated by 26% from July 2005

to July 2015. After 2015, China started to witness an exchange rate appreciation, the USD/CNY increased by 1.9% in august 11, 2015. During the same period of the exchange rate's appreciation the Chinese stock market experienced volatile price swings (IMF, 2019). These events suggest an existence of interrelation between the exchange rate and the stock market in China.

The theoretical linkage between exchange rate and stock prices can be explained using two main classical models, the flow-oriented model and the stock-oriented model.

The flow-oriented model presented by Dornbusch and Fisher (1980) a causal relationship running from exchange rate to stock prices. The model indicates that the effect of exchange rate on stock market is originated from the impact of exchange rate on the current account (trade balance) of a country. Dornbusch and Fisher (1980) argue that the international competitiveness of local firms is to a large extent affected by variations in exchange rate. Consequently, both imports and exports are affected which cause changes in the country's current account and income level. In other words, the depreciation of domestic currency increases exports by making exporting goods cheaper for international consumption. Higher exports level leads to higher income level and since stock's price is the present value of firm's future cash flow, the increase in income induces an increase in stock prices.

The alternative model which represents the relation between stock prices and exchange rate is the stock-oriented model developed by Branson et. al. (1983) and Frankel (1983). This model advocates a causal relationship running from stock market to exchange rate. An increase in stock prices leads to an increase in the demand for domestic currency as a result of an increase in the demand for domestic financial assets. The exchange rate is

represented as the price that equates demand and supply for financial assets (i.e.: stocks). Therefore, the higher the demand for domestic assets the lower is the exchange rate. Moreover, an indirect effect of the rise in domestic stock prices on the exchange rate is postulated by this model as following. The increase in stock prices boosts investors' wealth, and the demand for money consequently. Higher money demand leads to higher domestic interest rate which persuades more foreign capital inflows. The higher foreign demand for domestic currency results in a depreciation in the exchange rate.

The previously mentioned events and theoretical models suggest the existence of causal relation between exchange rate and stock prices. Hence, The Chinese leaders' plan to decrease debt-to-GDP ratio by encouraging investment in stock market in order to boost wealth and raise funds to corporations, could be presumably affected by the exchange rate. Therefore, it's of great importance to study the effect of exchange rate on the Chinese stock prices for exchange rate policy suggestions. Moreover, the result of such study would help investors in making correct investment decisions when investing in Chinese stocks.

This project studies the effect of exchange rate on stock prices in China over a daily data sample from January 1, 2009 to January 1, 2019. The relation between exchange rate and stock prices is investigated using Johansen's approach test, Granger causality test, variance decomposition and impulse response methods employed in an unrestricted vector autoregressive model. The next chapters are presented as follows: Chapter II reviews related literature on the relation between exchange rates and stocks prices. Chapter III describes the data and methodology used in the empirical investigation. The empirical results and analysis are discussed in Chapter IV. Finally, Chapter V summarizes the findings of the project and offers policy implications.

#### CHAPTER 2

#### LITERATURE REVIEW

Several empirical studies investigated the relation between exchange rates and stock prices for different countries. However, they reported different results on the direction, type and significance of that relation.

Solnik (1987) studied the relation between exchange rates and stock markets in Japan, Germany, France, Switzerland, U.K, Netherlands, Canada, and USA over the 1973-1983 period when exchange rates were considered most flexible. By employing Multivariate regression analysis, he found a positive but weak effect of an increase in stock returns on the exchange rate in all the eight countries. Likewise, the results revealed by the study done by Li, Rong, et al. (2019) indicate a positive dependence coefficient between USD/RMB exchange rate and Chinese stock market returns. The relation between both variables appeared to be weak before 2008 financial crisis and become stronger afterward. To study the dependence between the Chinese stock market and the real RMB exchange rate, they used a Copula-GARCH approach over a daily data set from July 22, 2005 to December 31, 2017.

There exist other studies which indicate a negative relation between stock market and exchange rate. Kanas (2000) employed a bivariate EGARCH model and found a negative and significant correlation coefficient between exchange rate changes and stock returns in six industrial countries (Japan, France, Germany, US, Canada and U.K.). Likewise, Ahmed, Kashif and Feroz (2017) found that shocks in exchange rate have

negative and significant effect on stock returns in Pakistan. By conducting the variance decomposition test in a var model over monthly data set (from January 2005 to December 2015), They found that exchange rate variations cause 18.1% of the variations in stock returns, while variations in stock returns cause only 6.6% of variations in exchange rates. Blahun Ivan (2019) and Lee and Wang (2015)' findings also suggest that a negative relation between stock returns and exchange rate. Blahun Ivan (2019) investigated the impact of exchange rate changes on the stock market in Ukrain over the 2010-2017 period. He found a negative relationship between stock returns and exchange rate, one percent increase in stock returns leads to 0.03 percentage appreciation in the Ukrainian currency to USD. By employing PMG estimation method recommended by Pesaran et al. (1999) over a sample data set of 29 countries during the period 2000-2011, Lee and Wang (2015) found a negative relation between exchange rates and stock markets. Whereas for the long run, the exchange rates and stock markets were found to be positively correlated.

Moreover, Rashid (2008) and Yeap Lau and How Go (2018) show that there exists a significant linkage between stock returns and exchange rate without indicating the type of the relationship. Rashid (2008) run Granger causality and cointegration tests in a VECM model to investigate the dynamic interactions between the stock market in Pakistan and four macroeconomics variables; exchange rate, consumer prices, industrial production and interest rate. His results revealed a strong cointegration between stock prices and the four macroeconomics variables. A granger causality was found between stock prices and interest rates only. Moreover, the estimates of the bivariate models show a bidirectional causation between stock prices variable and each of exchange rate, industrial production and interest rate variables. Yeap Lau and How Go (2018) used the CCF approach

developed by Cheung and Ng (1996) to study the dynamic relation between exchange rate and stock returns in Malaysia over a daily sample data from July 2005 to July 2015. They found that stock returns Granger cause the exchange rate in mean and variance and they concluded that the stock-oriented hypothesis is maintainable in Malaysia.

Another bunch of researches investigated the linkage between stock markets and foreign exchange market by studying the volatility spillover effects between stock returns and exchange rates. In their study, Jebran and Iqbal (2016) investigated the volatility spillover effect between the foreign exchange market and the stock markets in China, India, Pakistan, Sri Lanka and Japan. They collected daily data from January 4, 1999 to January 1, 2014 and employed it in an EGARCH model. Their analysis suggests a bidirectional but asymmetric volatility spillover effect between foreign exchange market and Chinese stock market and a unidirectional volatility transmission from Indian stock market to foreign exchange market. While, no evidence has been found of volatility spillover effect between the foreign exchange market and stock market in Japan. Fengming Qin, Junru Zhang & Zhaoyong Zhang(2018) examined the volatility spillover effects between both the Chinese and Japanese stock markets and the RMB foreign exchange market by employing the BEKK GARCH-M model on daily data of RMB/JPY, RMB/USD, and stock returns over 20 years period (1998-2018). They found a significant negative volatility spillover effect from the RMB/USD shocks into both the Chinese and the Japanese stock markets. Additionally, the findings of Kearney (1998) and Kumari and Mahakud (2014) support a significant volatility spillover effect from exchange rate into the stock market in Ireland and India. To estimate the linkage between exchange rate and Indian stock Market Kumari and

Mahakud (2014) used two stage estimation techniques over 17 years period (July 1996-2013).

In contrast with the previous studies, which suggest a significant linkage between exchange rate and stock market, some other studies find no evidence of significant relation between the two. Jorion (1991) used two-factor and multi-factor arbitrage pricing models to investigate the impact of exchange rate risk on the U.S stock market and found no spillover effect from exchange rate into the U.S stock market. The empirical results show a very small and insignificant unconditional exchange rate risk premium which indicates that exchange rate risk is not priced in the stock market. In addition, Nieh and Lee (2001) analyzed the relationship between exchange rates and stock markets for G-7 countries by employing a VECM model over daily sample data covering the period from October 1, 1993 to February 15, 1996. Their results reveal no significant long-run correlation between stock markets and exchange rates in all the G-7 countries in the long run. However, there's only a one-day significant relationship for some G-7 countries. Hartmann and Pierdzioch (2007) also found no significant linkage between exchange rate and Japanese stock market by examining monthly data sample of Japanese stock returns and the Yen to U.S Dollar exchange rate (Yen/USD) covering the period 1991-2005.

As for the papers that studied the relation between exchange rate and stock market in China, some reported the absence of this relation while others confirmed its existence. In the latter case both unidirectional and bidirectional spillover effects have been found. Besides, some literature suggested a positive relation, while others suggested a negative one. Wei (2008) estimated the impact of the unexpected exchange rate's shock and volatility spillover to stock market in China using MGARCH-M model and daily data set

from July 21, 2005 to January 4, 2007. He found a negative correlation between the unexpected shock in USD/RMB exchange rate and the Chinese stock returns and a significant volatility transmitted effect from exchange rate market to stock market. In addition, Zhao (2010) run VAR and GARCH models to examine the dynamic relationship between renminbi real effective exchange rate and the Chinese stock market. He used a monthly data from January 1991 to June 2009 and found no significant direct relation between exchange rate and stock prices in China but there are bidirectional volatility spillover effects between the two variables. In addition, Nieh and Yau(2010) investigated the relationship between renminbi appreciation and stock prices in China since the removal of the peg in 2005 by employing daily data, from July 21, 2005 to September 30, 2008, on the Chinese Shanghai A-share stock prices and the USD/RMB nominal closing exchange rate in an Error correction model. They found that the renminbi appreciation has a significant effect on stock prices in the long run only. Likewise, The study investigated by Sui and Sun(2016) supported a unidirectional causal relation running from exchange rates to stock returns in the BRICS countries which adopt a managed floating exchange rate regime, by using a VAR and VECM models over monthly data from July 2005 to August 2014 for China. Guangxi Cao (2012) used TVP-VAR to study the time varying effects of changes in Renminbi exchange rate and interest rate on China's stock market over a daily data sample from July 22, 2005 to January 13, 2012. According to the empirical results, the responses of Chinese stock returns to shocks in RMB exchange rate are sensitive to the reform done in June 2010 which increased the flexibility of the RMB exchange rate. Moreover, he found a negative relation between RMB exchange rate and Chinese stock returns in both long term and short term. However, the effect is stronger in the long term. In

contrast, Ahalawat and Patro (2019) suggested a positive relation between the exchange rate and Chinese stock prices in the short run after conducting variance decomposition and impulse response approaches in a vector autoregressive (VAR) model employed on monthly data from January 2009 to December 2010. Whereas, they found no significant relation between the two variables in the long run.

We can observe that some studies found a significant relationship between exchange rate and stock prices (Solnik (1987 Li, Rong, et al. (2019), Ahmed, Kashif and Feroz (2017), Kanas (2000), lee and Wang (2015), Blahun Ivan (2019), Rashid (2008), Yeap Lau and How Go (2018)). Some of the relations founded to be positive (Solnik (1987), Li, Rong, et al. (2019), Ahalawat and Patro (2019)), while others were negative (Kanas (2000), Ahmed, Kashif and Feroz (2017), Blahun Ivan (2019), lee and Wang (2015)).

On the other hand, some studies found no evidence of exchange rate's effect on stock market (Jorion (1991), Nieh and Lee (2001), Hartmann and Pierdzioch (2007)). These contradictory results have been obtained even when the same country is studied, particularly for China. Several studies suggested a negative spillover effect of the exchange rate on the Chinese stock market (Wei(2008), Guangzi Cao(2012)), others argued that this effect is positive (Ahalawat and Patro (2019)), and some other studies found that effect to be negligible (Zhao(2010)). Since the impact of exchange rate on stock prices in China is still not clear, this project studies the relation between the USD to Chinese Yuan exchange rate and the Chinese stock market in an attempt to add more empirical evidence to the previous findings.

### CHAPTER 3

#### METHODOLOGY

#### **3.1.** Variables and Data Description

Our model investigates the effect of exchange rate on Chinese stock prices over the period between January 1, 2009 and January 1, 2019. We analyze daily data for closing price of the Chinese Yuan to U.S. Dollar exchange rate and of the Shanghai Stock Exchange Composite (SSEC) Index using the EViews 10 statistical software. The exchange rate is represented in terms of numbers of Chinese Yuan per unit of USD (USD/CNY). The SSEC index is used as proxy for the Chinese stock prices since it's considered the leading stock market indicator of China, following all Class A and B shares listed on the Shanghai stock exchange. The daily data samples of both variables are obtained from Thomson Reuters website. The USD/CNY price variable is symbolized as ER, while the SSE composite index price variable is symbolized as SP in our Model. Both variables are expressed in natural logarithms. We use VAR model and we limit our analysis to a bivariate one.

#### **3.2. Methodological Tests**

#### 3.2.1 Unit Root Test

A stationary variable is a variable which variance and mean do not change with change of time. It's crucial to have stationary variables in the Var model in order to get efficient inferences results. Therefore, before running our Var model the ADF (Augmented Dickey Fuller) and the PP (Phillips Perron) are employed to test for stationarity of stock price variable (SP) and exchange rate variable (ER). Both tests are based on the following equation:

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \theta t + \sum_{i=1}^p \varphi_i \Delta Y_{t-1} + \varepsilon_t \quad (1)$$

A is the intercept,  $\theta$  is the coefficient of the time trend,  $\varepsilon_t$  is a white noise error term and p is the number of lags which is selected by the Akaike information criterion from a maximum number of lags based on Schwert's formula  $T_{max} = 12 \times \left(\frac{T}{100}\right)^{\frac{1}{4}}$ .

Two Different specifications of the model will be used while running both tests. One specification is with intercept only, and the other with intercept and time trend. The null hypothesis for both tests is Ho:  $\Upsilon=0$  (the variable Y has a unit root), and the alternative hypothesis is H1:  $\Upsilon < 0$  (the variable Y is stationary). The critical values are taken from MacKinnon since the distribution of  $\Upsilon$  does not follow the conventional t-distribution. If a variable is found to be stationary in level, then it's integrated of order zero I(0). While, If the variable is found to be non-stationary in level, we should proceed by taking its first difference which is the difference between the variable at time t and its lagged value. After taking the first difference we should test again for unit root. If the variable is stationary in its first difference therefore it's declared to be integrated of order 1 I(1). If unit root tests indicate that both variables are integrated of order one I(1) or at least one of them is I(1) we

must therefore test for the existence of cointegration relation between the variables before proceeding with Var analysis.

#### 3.3.2 Cointegration Test

Cointegrated variables are variables bound by a long run relation. To test for cointegration we will use Engle and Granger's test complemented by Johansen's approaches test. If the cointegration tests indicate that the variables are cointegrated, we must use VECM (vector error correction model) to investigate the relation between them. Whereas, if the variables are not cointegrated we can take their first differences and continue by employing them in the unrestricted VAR model.

#### 3.3.3 Unrestricted VAR Model

Vector autoregression (VAR) model proposed by Sims (1980) is used to capture the linear interdependencies among multiple time series. Each variable in a VAR model has an equation explaining its evolution based on its own lagged values, the lagged values of the other variables, and an error term. All variables in a VAR model are treated as endogenous variables. Granger-causality test, impulse response function and variance decomposition are widely used in this model to investigate the dynamics of the relation between the variables.

The VAR model in reduced form is given by the following equation:

$$Y_t = c + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + u_t \quad (2)$$

- $Y_t$  is a k × 1 vector of the k stationary variables of the model
- $Y_{t-p}$  is vector of lagged variables of the model
- $A_i$  is and k × k parameter matrices
- $u_t$  is a k × 1 vector of white noise error terms
- P is the number of lags and

Since estimates of a VAR whose lag length differs from the true lag length are inconsistent as are the impulse response functions and variance decompositions derived from the estimated VAR, the process of choosing the maximum lag p requires special attention. To determine the optimal lag length, we will follow the Akaike information criterion where the maximum number of lags is calculated based on Schwert's formula  $T_{max}$ = $12 \times (\frac{T}{100})^{\frac{1}{4}}$ . Afterward, to confirm the chosen lag length, lag exclusion Wald tests will be conducted.

#### 3.3.4 Granger Causality Test

Granger causality is a statistical concept of causality that is based on prediction. According to Granger causality, if  $X^1$  "Granger-causes"  $X^2$ , then past values of  $X^1$  should contain information that helps predict  $X^2$  above and beyond the information contained in past values of  $X^2$  alone.

Consider the following two equations:

$$X_{t}^{1} = A_{0}^{1} + \sum_{i=1}^{p} A_{1i}^{1} X_{t-1}^{1} + \sum_{i=1}^{p} A_{2i}^{1} X_{t-1}^{2} + u_{t}^{1} \quad (3)$$
$$X_{t}^{2} = A_{0}^{2} + \sum_{i=1}^{p} A_{1i}^{2} X_{t-1}^{2} + \sum_{i=1}^{p} A_{2i}^{2} X_{t-1}^{1} + u_{t}^{2} \quad (4)$$

P is the number of lags and the matrix A contains the coefficients of the model.  $u^1$  and  $u^2$  are white noise error terms and all variables are stationary. If the variance of  $u^1$  is reduced by the inclusion of  $X^2$  term in equation (1), then it is said that  $X^2$  Granger causes  $X^1$ . Similarly, for equation (2), if the variance of  $u^2$  is reduced by the inclusion of  $X^1$  term, then we can say that  $X^1$  Granger causes  $X^2$ . In other words,  $X^2$  ( $X^1$ ) Granger causes  $X^1$  ( $X^2$ ) if the coefficients in  $A_2^1(A_2^2)$  are jointly significantly different from zero. This can be tested by performing a Wald test. To study the causality between exchange rate and stock price in China the Granger causality test will be applied in the unrestricted Var model.

#### 3.3.5 Impulse Response Function (IRF)

Impulse response function (IRF) is an essential tool in empirical causal analysis. It's used to describe the response of one variable to a shock in another variable at the time of the shock and over subsequent periods in time. We will use this tool to investigate the impulse response of one variable to an innovation in another variable. For instance, to track the response of stock prices to a shock in exchange rate, a one period shock will be introduced to exchange rate variable by increasing the error term by one standard deviation at time zero and then we can track out the impact of this impulse on stock price variable instantly and several periods later. A problematic assumption in this type of impulse response analysis is that a shock occurs only in one variable at a time. However, if the error terms are correlated, a shock in one variable is likely to be accompanied by a shock in another variable. Orthogonalized impulses based on the Cholesky decomposition could be used to isolate the effects of any specific shock and solve this problem. The ordering of the variables determines the impulse responses and it's therefore critical for the interpretation of the system. The variable with potential impact on all other variables should be placed first.

#### 3.3.6 Variance Decomposition

Variance decomposition is another tool that will be used to aid further in the interpretation of the relation between stock price variable and exchange rate variable in our vector autoregression model. This method determines the percentage of the variation in one variable that is explained by its own shock as well as the remaining percentages caused by other exogenous shocks to other variables in the model. Thus, while impulse response functions track the effects of a shock to one endogenous variable on other variables, variance decomposition method separates the variation in one endogenous variable in response to different shocks to the VAR variables. The order of the variables is also important while running the VAR variance decompositions. The variable that has potential effect on the other variables should be placed first.

#### CHAPTER 4

#### EMPIRICAL RESULTS

#### **4.1. Unit Root Tests Results**

#### 4.1.1 Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Tests

We begin our analysis by testing for unit root using both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The optimal lag length for the ADF test is automatically determined based on the Akaike Information Criterion and the bandwidth for the Philips-Perron test is selected using a Newey-West automatic bandwidth selection criterion for the PP test. We test for unit roots for exchange rate series (ER) and stock price series (SP) in both level and first difference using two separate test equations, one with intercept only and the other with intercept and trend. The null hypothesis for both ADF and PP tests is the existence of a unit root, so if the series is stationary I(0), the ADF and PP tests should reject the null hypothesis. The results for the two tests when variables are in their level and their first difference are reported in table 1 and 2 respectively. In table 1, we can observe that the p-values for both SP and ER variables are greater than 0.05, therefore we fail to reject the null of the existence of unit root at level for stock price and exchange rate variables at 5% level of significance. As for first difference, the results of both tests in table 2 indicate a rejection of the hull hypothesis for both exchange rate (ER) and stock price (SP) at 5% level of significance since the p-values are less than 0.05. Therefore, we can conclude that the two series are integrated of order one I(1). Since both ER and SR

series are integrated of order one, we must test for cointegration relation between the two series before proceeding with the VAR model.

Level						
	AD	F statistics	PP	' statistics		
Variable	Intercept	Trend and Intercept	Intercept	Trend and Intercept		
SP	-2.405354 (0.1403)	-2.269109 (0.4503)	-2.556091 (0.1025)	-2.308333 (0.4287)		
ER	-1.542649 (0.5119)	-1.426398 (0.8533)	-1.047814 (0.738)	-0.876555 (0.9569)		

Table 1: Results of ADF and PP Tests at Level

Note: MacKinnon (1996) one-sided p-values are in parenthesis.

1 able 2. Results of AD1 and 11 tests at 1 list Difference
------------------------------------------------------------

First Difference						
	ADF statistics		PP	statistics		
Variable	Intercept	Trend and	Intercept	Trend and		
		Intercept		Intercept		
	-10.04551	-10.07623	-49.051646	-49.52583		
SP	(0.0000)	(0.0000)	(0.0001)	(0.0000)		
	-7.572872	-7.715940	-50.89638	-50.89638		
ER	(0.0000)	(0.0000)	(0.0001)	(0.0001)		

Note: MacKinnon (1996) one-sided p-values are in parenthesis.

#### **4.2.** Cointegration Tests Results

#### 4.2.1 Engle and Granger and the Johansen Tests

Next, we test for cointegration relation between the two series by employing both the Engle and Granger and Johansen's approach tests. The null hypothesis for Engle and granger's test is the absence of cointegration relation between our variables. Since the pvalues of the variables in for both models are greater than 0.05 (results in table 3) we fail to reject the null hypothesis and we conclude that ER and SP series are not cointegrated. Similarly, Both the Maximum Eigenvalue and Trace statistics for the Johansen's approach test indicate that there's no cointegrating relation between the two variables (results in table 4). Since no cointegration relation has been found between ER and SP we can conclude that there's no long-run stable relation between exchange rate and stock prices in China.

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
ER	-1.610057	0.7184	-4.238009	0.7920
SP	-2.839828	0.1537	-11.75629	0.2705

Table 3: Results of Engle-Granger Cointegration Test

#### Table 4: Johansen Cointegration Test summary

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	0	0	0	0
Max-Eig	0	0	0	0	0

Selected (0.05 level\*) Number of Cointegrating Relations by Model

\*Critical values based on MacKinnon-Haug-Michelis (1999)

#### 4.3. Unrestricted Variance Autoregressive Model (VAR)

#### 4.3.1 Lag Length Determination and Lag Exclusion Wald Tests Results

Since both ER and SP are integrated of order one and not cointegrated, we can proceed with taking the first difference of both variables in an unrestricted Var Model. Knowing that the Var analysis are sensitive to the number of lag length, we choose the appropriate lag length based on the Akaike Information criterion. According to ACI criterion, the appropriate lag order for our model is 9. As we can observe from table 5, two other different criterion, Final prediction error (FPF) and sequential modified LR test statistic, also agreed on the optimal lag order.

Lag	LogL	LR	FPE	AIC	SC
0	20455.11	NA	4.98e-10	-15.74527	-15.74076*
1	20457.76	5.289416	4.98e-10	-15.74423	-15.73069
2	20459.47	3.429134	4.99e-10	-15.74247	-15.71991
3	20461.93	4.890183	5.00e-10	-15.74128	-15.70969
4	20465.57	7.267599	5.00e-10	-15.74101	-15.70039
5	20468.68	6.196432	5.00e-10	-15.74033	-15.69068
6	20474.66	11.89152	4.99e-10	-15.74185	-15.68318
7	20483.25	17.08257	4.98e-10	-15.74538	-15.67769
8	20487.88	9.191701	4.97e-10	-15.74586	-15.66914
9	20497.83	19.76349*	4.95e-10*	-15.75045*	-15.66470
10	20499.09	2.490160	4.96e-10	-15.74833	-15.65356

Table 5: VAR Lag Order Selection Criteria

\* indicates lag order selected by the criterion
 LR: sequential modified LR test statistic (each test at 5% level)
 FPE: Final prediction error
 AIC: Akaike information criterion

SC: Schwarz information criterion

Afterward, a lag exclusion Ward tests are conducted to confirm the chosen lag length. The results of the Wald tests are reported in table 6. The joint null hypothesis for exclusion of the 9<sup>th</sup> length is rejected, while the joint hypothesis for exclusion of the 10<sup>th</sup> lag is accepted at 5% level of significance. Therefore, we can proceed by including 9 lags in our unrestricted Var model.

	D(ER)	D(SR)	Joint
Lag 1	1.177103	3.200903	4.645404
	[ 0.5551]	[ 0.2018]	[ 0.3257]
Lag 2	2.889655	1.739623	4.238844
	[ 0.2358]	[ 0.4190]	[ 0.3746]
Lag 3	4.381765	0.533662	4.744613
	[ 0.1118]	[ 0.7658]	[ 0.3145]
Lag 4	2.372858	2.856098	5.235005
	[ 0.3053]	[ 0.2398]	[ 0.2640]
Lag 5	4.613547	1.208676	5.637391
	[ 0.0996]	[ 0.5464]	[ 0.2279]
Lag 6	3.445712	10.31059	12.85558
	[ 0.1786]	[ 0.0058]	[ 0.0120]
Lag 7	4.110329	15.73592	18.53245
	[ 0.1281]	[ 0.0004]	[ 0.0010]
Lag 8	2.290999	6.360706	8.352622
	[ 0.3181]	[ 0.0416]	[ 0.0795]
Lag 9	12.77697	8.612783	19.86088
	[ 0.0017]	[ 0.0135]	[ 0.0005]
Lag 10	2.187898	0.181894	2.491311
	[ 0.3349]	[ 0.9131]	[ 0.6462]

Table 6: VAR Lag Exclusion Wald Tests

Note: Chi-squared test statistics for lag exclusion

The estimated VAR model is as follows:

$$\begin{split} D(ER) &= C(1,1)^*D(ER(-1)) + C(1,2)^*D(ER(-2)) + C(1,3)^*D(ER(-3)) + \\ C(1,4)^*D(ER(-4)) + C(1,5)^*D(ER(-5)) + C(1,6)^*D(ER(-6)) + C(1,7)^*D(ER(-7)) + \\ C(1,8)^*D(ER(-8)) + C(1,9)^*D(ER(-9)) + C(1,10)^*D(SP(-1)) + C(1,11)^*D(SP(-2)) + \\ C(1,12)^*D(SP(-3)) + C(1,13)^*D(SP(-4)) + C(1,14)^*D(SP(-5)) + C(1,15)^*D(SP(-6)) + \\ C(1,16)^*D(SP(-7)) + C(1,17)^*D(SP(-8)) + C(1,18)^*D(SP(-9)) + C(1,19) \end{split}$$

$$\begin{split} D(SP) &= C(2,1)^* D(ER(-1)) + C(2,2)^* D(ER(-2)) + C(2,3)^* D(ER(-3)) + \\ C(2,4)^* D(ER(-4)) + C(2,5)^* D(ER(-5)) + C(2,6)^* D(ER(-6)) + C(2,7)^* D(ER(-7)) + \\ C(2,8)^* D(ER(-8)) + C(2,9)^* D(ER(-9)) + C(2,10)^* D(SP(-1)) + C(2,11)^* D(SP(-2)) + \\ C(2,12)^* D(SP(-3)) + C(2,13)^* D(SP(-4)) + C(2,14)^* D(SP(-5)) + C(2,15)^* D(SP(-6)) + \\ C(2,16)^* D(SP(-7)) + C(2,17)^* D(SP(-8)) + C(2,18)^* D(SP(-9)) + C(2,19) \end{split}$$

#### 4.4. Serial correlation test results

To make sure that there's no residual serial correlation in our model we conduct the VAR residual serial correlation LM tests. The null hypothesis of this test is the absence of residuals serial correlation at lags 1 to h. The results are reported in table 7. We can observe from the table that the probabilities of both LRE and RAO statistics of lag one up to all included nine lags are greater than 0.05. Therefore, we don't reject the null hypothesis at 5% level of significance at all lags, and we conclude that there's no residuals autocorrelation in our VAR model.

Lag	- LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	2.480034	4	0.6482	0.620037	(4, 5154.0)	0.6482
2	3.353546	8	0.9103	0.419086	(8, 5150.0)	0.9103
3	9.066978	12	0.6972	0.755513	(12, 5146.0)	0.6972
4	11.61868	16	0.7698	0.725999	(16, 5142.0)	0.7698
5	20.56774	20	0.4230	1.028643	(20, 5138.0)	0.4230
6	22.11107	24	0.5726	0.921303	(24, 5134.0)	0.5726
7	29.62456	28	0.3814	1.058391	(28, 5130.0)	0.3814
8	31.89011	32	0.4722	0.996747	(32, 5126.0)	0.4722
9	37.53711	36	0.3986	1.043053	(36, 5122.0)	0.3986
10	50.19557	40	0.1296	1.256376	(40, 5118.0)	0.1296

Table 7: VAR Residual Serial Correlation LM Tests

*Null Hypothesis: no serial correlation at lags 1 to h. Edgeworth expansion corrected likelihood ratio statistic.* 

#### 4.5. Granger Causality Wald tests Results

To investigate the causal relation between exchange rate (ER) and stock price (SP) we conduct the Var Granger causality Wald tests. The results of the tests are reported in table 8. In the regression where D(ER) is the dependent variable, the probability of the null hypothesis of D(SP) equal to zero is less than 0.05, thus the null hypothesis is rejected at 5% level of significance. In contrast, when D(SP) is the dependent variable, we fail to reject the null hypothesis of D(ER) equals to zero at 5% level of significance. Hence, exchange rate Granger causes stock prices, but stock prices do not Granger cause exchange rate. We can conclude that there's a unidirectional causal relation running from the USD/CNY exchange rate to the Chinese stock prices in the short run. A change in the present price of the exchange rate in China can lead a change in stock prices in the following days. This result goes in line with the Flow-oriented model which suggests that movements in exchange rate affect stock prices via the country's current account. Based on our results, investors should pay close attention to the exchange rate movements when taking investment decisions. In addition, since the exchange rate in China is still not fully marketbased but managed by the PBOC in some occasions, the Chinese authorities should take into consideration the effect of exchange rate on the stock market when directing the exchange rate or when implementing exchange rate's policies.

Dependent variable: D(ER)				
Excluded	Chi-sq	df	Prob.	
D(SP)	9.090395	9	0.4290	
All	9.090395	9	0.4290	
Dependent variable: D(SP)				
Excluded	Chi-sq	df	Prob.	
D(ER)	21.62597	9	0.0101	
All	21.62597	9	0.0101	

Table 8: Results of Granger Causality Wald Tests

#### 4.6. Variance Decomposition Results Analysis

To study more the relation between exchange rate and stock market in China, we run the orthogonal variance decomposition. This method is used to determine how much of the forecast error variance of each of D(ER) and D(SP) variables can be explained by exogenous shocks to each variable. From the table 11 we can see that 99.08% of the variability in stock price variable D(SP) is attributed to its own innovation in the first day. This percentage declines slightly to 98.2% after 17 days and remains unchanged to the end of the 30-days period. Only 0.91% of the variability in D(SP) is caused by innovation in the exchange rate variable D(ER) in the first day. This percentage continues to increase slightly until it reaches 1.78% after 17 days and remains at this level till day 30. Hence, a shock in

the exchange rate affects the Chinese stock prices from day 1, but this effect appears to be the most significant at the 17<sup>th</sup> after the exchange rate's shock.

Variance D	Variance Decomposition of D(SP):			
Period	5.E.	D(ER)	D(SP)	
1	0 013849	0 917485	99 08252	
2	0.013858	0.930241	99.06976	
3	0.013862	0.969159	99.03084	
4	0.013863	0.975357	99 02464	
5	0.013871	0.974470	99 02553	
6	0.013875	1.005067	98,99493	
7	0.013902	1.046957	98.95304	
8	0.013940	1.561550	98.43845	
9	0.013959	1.557690	98.44231	
10	0.013979	1.762433	98.23757	
11	0.013979	1.765366	98.23463	
12	0.013979	1.765431	98.23457	
13	0.013980	1.771716	98.22828	
14	0.013980	1.771784	98.22822	
15	0.013981	1.775567	98.22443	
16	0.013981	1.775707	98.22429	
17	0.013981	1.783463	98.21654	
18	0.013982	1.784685	98.21531	
19	0.013982	1.786544	98.21346	
20	0.013982	1.786761	98.21324	
21	0.013982	1.786773	98.21323	
22	0.013982	1.786973	98.21303	
23	0.013982	1.786980	98.21302	
24	0.013982	1.787073	98.21293	
25	0.013982	1.787121	98.21288	
26	0.013982	1.787226	98.21277	
27	0.013982	1.787266	98.21273	
28	0.013982	1.787282	98.21272	
29	0.013982	1.787288	98.21271	
30	0.013982	1.787290	98.21271	

Table 9: Variance Decomposition of Stock Price Variable

The variance decomposition results for exchange rate variable D(ER) in table 12 reveals that 100% of the variability in D(ER) is explained by its own innovation in day 1. This percentage decreases very slightly to 99.62% after 15 days and remains at this level

till the end of the 30-days period. The variability in D(ER) from innovations in D(SP) variable is negligible. Therefore, changes in stock prices in China does not influence the exchange rate.

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Varia <del>nce</del> D Period	ecomposition of S.E.	D(ER): D(ER)	D(SP)
		. ,	. ,
1	0.001602	100.0000	0.000000
2	0.001602	99.96268	0.037316
3	0.001603	99.92589	0.074109
4	0.001604	99.92467	0.075329
5	0.001605	99.92371	0.076291
6	0.001607	99.87948	0.120516
7	0.001608	99.72654	0.273462
8	0.001609	99.68835	0.311646
9	0.001610	99.64338	0.356617
10	0.001614	99.63750	0.362504
11	0.001614	99.63288	0.367124
12	0.001614	99.63288	0.367124
13	0.001614	99.63152	0.368478
14	0.001614	99.63022	0.369778
15	0.001614	99.62702	0.372984
16	0.001614	99.62690	0.373101
17	0.001614	99.62569	0.374305
18	0.001614	99.62558	0.374423
19	0.001614	99.62527	0.374732
20	0.001614	99.62526	0.374742
21	0.001614	99.62524	0.374764
22	0.001614	99.62524	0.374763
23	0.001614	99.62517	0.374826
24	0.001614	99.62516	0.374845
25	0.001614	99.62515	0.374851
26	0.001614	99.62514	0.374857
27	0.001614	99.62514	0.374858
28	0.001614	99.62514	0.374860
29	0.001614	99.62514	0.374860
30	0.001614	99.62514	0.374860

Table 10: Variance Decomposition of Exchange Rate Variable

From the variance decomposition results we can conclude that changes in stock prices is driven by exchange rate shocks in China, but the percentage of the effect is very low. The percentage of the forecast error variance of stock price variable attributed to innovation in exchange rate variable reached a maximum of 1.787% only.

#### 4.7. Orthogonalized Impulse Response Function Results Analysis

Finally, we examine the dynamic interaction between the exchange rate and Chinese stock prices using the orthogonalized impulse response function. The order of the variables is crucial to the results of IRF. The variable that potentially influences the other variable should be placed first when running the Var model. Since we need to study the effect of exchange rate on the Chinese stock prices, we place exchange rate variable D(ER) before stock price variable D(SP) in the model. Figure 1 depicts the plot of the impulse response of stock price, from a Cholesky one standard deviation innovation in exchange rate. While, Figure 2 shows the impulse response of exchange rate from a Cholesky one standard deviation innovation in stock price. The responses of both variables are showed for horizons up to 30 days and the standard error confidence intervals are indicated by red dashed lines.

Response of D(SP) to D(ER)



Figure 1: Orthogonalized Impulse Response of Stock Price to Innovations in Exchange Rate





Figure 2: Orthogonalized Impulse Response of Exchange Rate to Innovations in Stock Price

From figure 1 we can observe that stock price D(SP) responds contemporaneously and negatively to a shock in exchange rate D(ER). The response becomes positive after 2 days and continues by varying between negative and positive until it disappears on day 11. On the other hand, figure 2 shows a positive response of exchange rate D(ER) after one day of a shock in stock price D(SP). The response lasts 2 days then it goes back to zero. However, a positive response reappears on the 6<sup>th</sup> day, it becomes negative on the 8<sup>th</sup> day until it disappears on the 10<sup>th</sup> day. As for the magnitudes of the responses presented in table 9 and table 10, we can obviously observe that they are hardly significant for both series.

Response of D(SP):				
Period	D(ER)	D(SP)		
1	-0.001327	0.013786		
	(0.00027)	(0.00019)		
2	-0.000163	0.000459		
	(0.00027)	(0.00027)		
3	0.000275	-0.000198		
	(0.00027)	(0.00027)		
4	-0.000111	0.000152		
	(0.00027)	(0.00027)		
5	-2.04E-05	0.000466		
	(0.00027)	(0.00027)		
6	-0.000245	0.000191		
	(0.00027)	(0.00027)		
7	0.000298	-0.000814		
	(0.00027)	(0.00027)		
8	-0.001006	0.000232		
	(0.00027)	(0.00027)		
9	2.46E-05	0.000721		
	(0.00027)	(0.00027)		
10	-0.000640	0.000406		
	(0.00027)	(0.00027)		
11	-7.67E-05	-5.33E-05		
	(6.2E-05)	(6.1E-05)		
12	1.15E-05	-1.34E-05		
	(6.1E-05)	(5.8E-05)		

Table 11: Orthogonalized Impulse Response of Stock Price to Innovations in Exchange Rate

Note: Cholesky Ordering: D(ER) D(SP) Analytic Standard Errors are in Parenthesis

Response Period	of D(ER): D(ER)	D(SP)
1	0.001602	0.000000
2	(2.2E-05) 1.60E-05	(0.00000) 3.10E-05
2	(3.1E-05)	(3.1E-05)
3	-4.59E-05 (3.1E-05)	(3.1E-05)
4	6.28E-05 (3 1E-05)	-5.86E-06 (3.1E-05)
5	5.16E-05	-5.18E-06
6	(3.1E-05) 5.66E-05	(3.1E-05) 3.38E-05
7	(3.1E-05) 5.21E-06	(3.1E-05) 6.29E-05
	(3.1E-05)	(3.1E-05)
8	5.33E-05 (3.1E-05)	-3.16E-05 (3.1E-05)
9	4.48E-05	-3.43E-05
10	0.000112	1.41E-05
11	(3.2E-05) 4.87E-06	(3.1E-05) 1.10E-05
12	(7.5E-06)	(6.3E-06)
12	(7.5E-06)	(6.1E-06)

Table 12: Orthogonalized Impulse Response of Exchange Rate to Innovations in Stock Price

Note: Cholesky Ordering: D(ER) D(SP) Analytic Standard Errors are in Parenthesis

The result of impulse response function reveals a negative response of stock prices to a positive shock in exchange rate.

Although our findings suggest a unidirectional relationship that goes from exchange rate to stock prices, they do not completely go along with the Flow-oriented model of exchange rate which suggests a positive relation between exchange rate and stock prices. The flow-oriented model argues that a local currency depreciation enhances the international competitiveness of domestic firms as its exports become cheaper, leading to an increase in exports and income, thereby an increase in stock prices. The negative effect of the appreciation in the USD to Yuan exchange rate (the depreciation in Yuan) on stock prices in China found by our model can be explained as follows:

First, the stock market in China might be driven in the short run by investors' expectations rather than macroeconomic fundamentals. A depreciation in domestic currency leads to higher imports prices and creates inflation in the economy. Inflation deteriorates the consumer's ability to spend, thereby reduces firms' cash flow and stock prices. Therefore, Inflation is considered a bad signal for stock market. As Chinese Yuan depreciates, Investors expect higher level of inflation in China and refrain from buying Chinese stocks, hence Chinese stock prices decline. This explanation is supported by the investigation done by Ajayi and Mougoue (1996), where they found a negative effect of the exchange rate's appreciation on stock prices in the short run. In addition, investors are discouraged from holding stocks in depreciating currency to avoid eroding returns. Stock prices drops subsequently.

Furthermore, the fear of the US-China trade war after the Yuan's depreciation would make domestic and international investors skeptical about investing in the stock market in China, leading to a decline in Chinese stock prices. Any devaluation of the Chinese currency is considered by the U.S administration a Chinese manipulation tool to gain unfair competitive advantage in international trade. The possible U.S. Sanctions on China as response to the Yuan's depreciation will deteriorate the Chinese economy. According to the New York Times, after an increase in the USD to Yuan exchange rate in 2015 the Chinese stock market witnessed prices decline as investors feared possible imposition of U.S tariff on Chinese imports (The New York Times, 2019).

Second, the suggestion raised by the flow-oriented model about the dynamic between exchange rate and stock prices is applicable in the case of exporting companies. While importing companies endure more costs as local currency depreciates since imported inputs become more expensive, resulting in a decline in their stock prices. In our model the SSE composite index is taken as proxy for the Shanghai stock exchange, which is the weighted average of all the A-shares and B-shares prices in the stock market, therefore any decrease in stock prices of importers caused by the currency's depreciation could outweigh the increase in the sock prices of exporters, leading to a negative net effect in the SSE composite index. Even though China is an export-based country, we can't assume that most companies available for trade are exporters since not all domestic companies are listed in the Shanghai stock exchange.

Finally, the ineffective stock market in China could be an additional reasonable explanation of the contradiction between the flow-oriented model implications and our findings. China's stock market does not reflect the Chinese economic state for its recently established (established in 1990) and it's not as developed as the western stock markets. The total value of traded stocks account for only 1/3 of China's GDP level. Only 7% of the whole Chinese population own and trade stocks. Also, 80% of these traded stocks are owned by a little number of investors which lead to volatile fluctuations in stock prices. In addition, most household investments are in real estate. According to Gavekal Dragonomics, only 5% of total household wealth is invested in Chinese stocks. Besides, a

low portion of companies' fund raising is achieved through stock financing and not all companies are listed in the stock market. Hence, the domestic companies are inadequately represented in the stock market. Moreover, in their study, Meng Chen et. Al (2004) found evidence that Chinese investors make poor trading decisions since the stocks they sell often outperform the stock they buy. Therefore, any effect on stock prices resulting from the irrational investors decisions will be misleading.

## CHAPTER V CONCLUSION

## Massive government spending has been the main driver of China's exceptional growth rate for 30 years. Besides, the tightly controlled exchange rate by the POBC, gave China a trade advantage over the US by reducing Chinese exports prices. However, the debt-to-GDP ratio hit a very high record. Also, low interest rates encouraged borrowing which led to asset bubble and inflation. Low returns on saving accounts caused by low interest rates resulted in low domestic consumption. These factors slowed down the growth rate. To save China from possible economic crisis, the Chinese leaders announced a longterm plan for economic reform in 2013. The economic reform consists of shifting from the dependency on government spending and low-price exports towards higher domestic consumption and private investment. But after the economic reform's announcement, China has been experiencing a further decline in growth rate. Fearing from the deterioration in standard of living, China's authorities are encouraging investment in stock market in order to boost wealth and growth rate. Since there exists a relation between exchange rate and stock market as suggested by two theoretical models, the flow-oriented model and the stock-oriented model, it's of great importance to study the effect of exchange rate on the Chinese stock market. This project investigates this relation over a daily data sample of USD/CNY and SSE composite index from January 1, 2019 to January 1, 2019 (post 2008)

financial crisis) by employing cointegration tests, Granger causality test, variance decomposition and impulse response functions in a VAR model.

Engle and Granger's test and Johansen's approach test reveal that there's no cointegration relation between our variables, hence there's no long run stable relation between exchange rate and stock prices in China. The Granger causality test indicates that exchange rate Granger causes stock prices. While, stock prices do not Granger cause the exchange rate. The Variance decomposition method reveals that a very high percentage of the variability in stock price are caused by its own innovation. Only 1.7% of the forecast error variance of stock price is attributed to innovation in the exchange rate in the first day. This percentage increases to only 1.7% afterward and remains at this level until the end of the 30-days period. Next, the orthogonalized impulse function is examined to study the dynamic interaction between exchange rate and stock prices. We find that stock prices respond contemporaneously and negatively to a positive shock in exchange rate. However, the response was minimal. Although, our results indicate a unidirectional causal relation that goes from exchange rate to stock prices as indicated by the flow-oriented model, the negative relation found by our model contradicts the positive relation suggested by the flow-oriented model. Possible explanations of a negative relation between exchange rate and stock prices in China could be as follows: First, in the short run the stock market could be affected by investors' expectations. Since a local currency depreciation leads to an increase in import prices, the investors would expect inflation and refrain from investing in the Chinese market after the Yuan's depreciation. Moreover, because of the US-China trade was any decrease in the Chinese exports prices after an appreciation in the USD to Chinese

Yuan exchange rate could leads to US sanctions in China. Therefore, Investors would be skeptical about investing in Chinese stocks fearing from possible U.S. sanctions on China. The abstention of domestic and foreign investors from investing in Chinese stocks will lead to a decline in Chinese stock prices. Second, the currency's depreciation decreases importers' stock prices, which can outweigh the increase in exporters' stock prices. This will be reflected in a decrease in the price of the SSE composite index. Third, the Chinese stock market does not perfectly represent China's economy and its ineffective (i.e., not all companies are listed in Shanghai stock exchange, irrational investors behavior) hence the Chinese stocks could be mispriced.

Finally, our findings have important implications. First, policymakers need to consider the impact of exchange rate changes on stock market in designing appropriate policy strategies. In the case of China, given that the exchange rate is no longer fixed, in order to boost wealth and increase growth rate the authorities should consider the impact of exchange rate changes not only on trade flows but also on stock market. Moreover, investors should watch exchange rate movements when making investment and portfolio management strategies.

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