ISCTE Business School
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THE RELATIONSHIP BETWEEN PROPERTY PRICES AND BANK LENDING IN CHINA

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Resumo

O objetivo desta pesquisa empírica, com base em séries temporais chinesas para o período compreendido entre o primeiro trimestre de 2001 e o quarto trimestre de 2016, é analisar, usando um modelo de correção de erros vetoriais (VECM) e causalidade à Granger, a interação dinâmica entre preços de imóveis e empréstimos bancários. Com o objetivo de estabelecer uma comparação, a análise dos Estados Unidos no período 2001Q1-2016Q2 também está incluída. Especificamente, foram realizadas quatro etapas. Em primeiro lugar, as variáveis da série temporal, incluindo os preços das propriedades, os empréstimos bancários, o PIB e a taxa de juro, foram determinadas com a ajuda do procedimento raiz de unidade aumentado Dickey-Fuller (ADF) e Phillips-Perron (PP). Em segundo lugar, examinou-se o grau de desfasamento ideal entre as variáveis no contexto da estrutura VAR. Em terceiro lugar, para determinar o número de relações de cointegração entre as variáveis, utilizou-se o teste de cointegração desenvolvido por Johansen e, em seguida, estabeleceu-se o VECM entre as variáveis do modelo. Finalmente, realizaram-se testes de causalidade de Granger com base no VECM para determinar a direção da causalidade entre as variáveis. Estes passos foram aplicados a ambos os países.

Este estudo mostra que há uma relação de cointegração entre os preços dos imóveis, os empréstimos bancários, o PIB, a taxa de juro tanto na China quanto nos EUA. Quanto à China, a direção da causalidade indica que o preço dos imóveis pode determinar os empréstimos bancários, mas os empréstimos bancários não parecem influenciar os preços da propriedade no longo prazo. Enquanto nos EUA, a relação é bidirecional.

Palavras-chave: Preços imobiliários, empréstimos bancários, PIB, taxa de juros, China
Sistema de classificação JEL: E51, R31

Abstract

The aim of this empirical research, based on Chinese time series data over the period 2001Q1-2016Q4 and using a vector error-correction (VECM) and Granger-causality test, is to analyze the dynamic linkage between property prices and bank lending. In contrast, the analysis of the United States over the period 2001Q1-2016Q2 is also included. Specifically, four steps were undertaken. Firstly, the time series variables including property prices, bank lending, the interest rate, and GDP were ascertained with the help of augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root procedure. Secondly, the optimal lag length among the variables was examined in the context of VAR framework. Thirdly, in order to determine the number of cointegration relationship among the variables we used the cointegration test developed by Johansen and then established the VECM according to the endogenous and exogenous variables. Finally, Granger-causality tests were undertaken based on the VECM to determine the direction of causality between variables of both countries.

This study shows that there is one cointegration relationship between property prices, GDP, bank lending, and the interest rate both in China and the U.S. As for China, the direction of causality runs from property prices to bank lending, which means that property prices can affect bank lending but bank lending does not seem to impact property prices in the long run. While for the U.S., the relationship is bidirectional.

Keywords: Property prices, bank lending, GDP, interest rate, China

JEL Classification System: E51, R31

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1. Introduction

It is said that the 2008 financial crisis in the United States results from sub-prime mortgage market which not only illuminates the outbreak of the U.S. property inflation in 2008 but also caused a global recession. Therefore, the development of the real estate market and property prices have become the focus of both economists and politicians over the world since then. On the one hand, to a large extent, the real estate market of China avoided the severe impact of this global crisis, on the other hand, the Chinese housing market itself has experienced dramatic overheating property prices for the last twenty years.

Actually, the real estate market in is China almost non-existence before the late 1970s. However, surprisingly, the property sector began to play an invisible role in the property financing system when Chinese government started innovation in policy in 1978. At that time, the socialist market economy was emerging gradually and an official document published in 1998 had a far-reaching impact on housing reform and construction.

To a certain extent, the Chinese housing market started very late, but it has developed rapidly after 1998 and has become a pillar industry in the Chinese economy nowadays. According to Xu, Jia, Li(2015), during 2001-2013, the added value created by the real estate industry contributes 4.3% per annum to economic growth. It was even up to 8.1% in 2007. Besides, Li (2014) argues that the National Bureau of Statistics released the latest data in 23rd September 2013 which said that the property prices rose in 69 large and medium-sized cities (there are 70 large and medium-sized cities altogether). In the most prominent performance of the first-tier cities, Beijing prices rose 19.3% in August, Shanghai rose 18.5%, Guangzhou rose 10%, and Shenzhen rose 18.4%.

From another perspective, with the rise in property prices, bank lending is also increasing. Huang, Leung, and Qu (2015) point that newly issued loans nearly 10 trillion yuan only in 2009, up 33% compared with the previous year and the total bank credit increased by 8 trillion yuan in 2010. Besides, after the financial crisis in 2008, the total amount of loans expanded by more than 50%. Actually, these loans and the 4 trillion yuan stimulus package should be used for financing infrastructure projects, but many counties eventually buy real estate at the expense of state-owned giants. Additionally, the U.S. housing market has a profound effect on undermining the stability of the financial system in the 2008 subprime mortgage crisis. According to Tajik et al. (2015), banks become more inclined to invest in the housing market because of skyrocketing property prices and low default rates, which in turn will lead to real estate bubble due to more and more speculative behavior in the housing market.

Also, it argues that the burst of the housing bubbles in the real estate brought tremendous pressure on the banks which were highly exposed to the housing market. Particularly, because of the sharp rise in bank non-performing, many banking institutions struggled with severe liquidity shortages. As concerns, the sustainability and soundness of economic development of China, the evaluation of the interaction between bank loans and house prices entails much attention. Moreover, in contrast to China, variables of the U.S. is analyzed as well.

Albeit there are already plenty of empirical studies on the issue of the relationship between house prices and bank credit, however, no agreement on the causal direction between them.

In sum, the contribution of this thesis is to improve the knowledge on the direction of the causality by measuring the link among bank lending, property prices, the interest rate, and GDP for China and the United States in a multivariate context in recent years based on the approach of VAR, VECM framework and finally utilized Granger-causality test

The structure of the study is as follows: the second chapter provides a brief literature review to describe the dynamic interaction between property prices and bank lending to better understand how it estimated; the third chapter describes and presents descriptive statistics of the data both for China and the United States in the model. Chapter four declares the empirical methodology. Empirical results are presented and discussed in chapter five. In this chapter, it analyzed the series behavior for both countries and the presentation of cointegrating equations will be done in this chapter as well. Finally, Chapter 6 summarizes the main results and draw conclusions.

2. Literature review

Since Chinese government processed economic reform policy which abolished original welfarism housing system in 1978 and started a trend of encouraging house ownership after 1998, according to Tsatsaronis and Zhu (2004), it argues that for most households, housing is becoming the largest single asset and its asset value which is also related to residential real estate has become an overriding part of the aggregate portfolio of financial intermediary. The property prices in China have risen unprecedented levels recently. What drives house price dynamics?

To answer the question we should analyze the determinants of the house price. There are several papers evaluated about it. These including Zou and Chau (2015), Égert and Mihaljek (2007), Stepanyan, Poghosyan, and Bibolov (2010), Tsatsaronis and Zhu (2004) and Zhu (2003). Zou and Chau (2015) put forward a concept of the sustainable house price. It refers that the price is stable and sustainable in the long run and middle-income families have the ability to afford, which can be rated by city, region or country. Besides, sustainable prices can be treated as long-term equilibrium prices. They believe that an equilibrium price is determined by macro fundamentals which including housing supply and demand, land, inflation rates, real estate returns, economic output, demographic factors and foreign investment. Égert and Mihaljek (2007) also believes those common determinants of house prices identified in the research act a pivotal part in explaining house price developments such as housing credit availability, real interest rate, real GDP and demographic factors. In addition, housing demand and supply determinants can be attributed to factors that can affect both long-term and short-term housing prices. According to Tsatsaronis and Zhu (2004), on the one hand, the long-term housing demand is influenced by the factors including the growth of household disposable income, gradual changes in demographic structure, the interest rate in the average level which may probably correlated to the inflation in the long-run, and several permanent characteristics exist in tax systems which could boost home ownership rather than other forms of wealth. On the other hand, long-term determinants of housing supply are determined by the construction costs, land availability and investment to improve the quality of existing housing stock. They also argue that idiosyncratic, national factors can lead to significant differences in house prices in the short-term. Besides, the provision of financing for purchasing the house is another crucial determinant which is also argued by Stepanyan, Poghosyan, and Bibolov (2010). It identifies that the development of property prices can be largely clarified by the dynamics of fundamentals such as gross domestic product, external financing, and remittances. Therefore, we can infer that property price can not only affect business cycles dynamics through aggregate expenditure but also affect the profitability and soundness of financial institutions. In general, housing purchase requires external financing, which means that the conditions of bank loans in shaping the dynamic model of housing prices played an important role. In another article, Zhu (2003) suggests that bank loans are the main source of real estate funds, thus it is not surprising that bank loans and house prices are closely related to each other. To be specific, if there is a sharp decrease in property prices it could seriously harm the quality and profitability of the financial institutions especially those who are highly related to the real estate industry. Also, the sharp decrease in property prices can reduce the bank lending capacity due to the higher risk of lower bank capital. Besides, to some extent, the fluctuation of property prices can be largely explained by the conditions of bank lending. If there is a lack of bank lending, the higher demand will lead to higher property prices while if the bank lending is abundant which means a higher supply of credit for house purchases, this will result in a possible decrease in property prices.

While considering the close interaction between property price and bank lending, Gorton and Metrick (2012) describes in the paper that the credit boom seems to coincide with rising property prices. Are financial intermediaries lowering lending standards so as to raise house prices? Or, property prices have increased because of some other reasons, and then intermediaries are willing to lend against collateral due to its current higher value?

In theory, the causality between bank lending and property prices do exist. However, there is no agreement on identifying the direction of the causality relationship between them. Many economists share with the idea of a bidirectional relationship between house prices and bank loans, such as Greef and Haas (2000), Hofmann (2003), Brissimis and Vlassopoulos (2009), Flannery and Lin (2015). In the case of Netherlands, Greef and Haas (2000) offer support of empirical evidence for the hypothesis that there exists in fact, a two-way causal relationship between property prices and bank lending. According to these authors, house prices and mortgage lending are interdependent. Changes in bank loans standards are said to have an impact on the property prices no matter the variables such as the housing stock, mortgage interest rate, disposable household income, demographic developments are controlled during the estimated period. Besides, both disposable income and bank loans Mortgage lending rely on the property prices as well. Hofmann (2003) utilizes econometric techniques and analyses the relationship between property prices and bank lending based on the time series from 20 countries. The results indicate that there exists a long-term causal relationship and changes in the property prices have a large impact on the bank loans which reflecting the changing beliefs about the uncertainty of future economic expectation drives the credit cycles. Furthermore, it estimates error-correction models (ECMs) and declares that there exist a bidirectional causality relationship in the short-run which implying the self-reinforce dynamics between house prices and bank credit. The empirical results consistent with the theory which describes in his paper that property prices have an effect on the availability of bank loans through the wealth effects. Firstly, because of the imperfection of financial market, the presupposition of bank lending is to put property as collateral which in turn determined the capacity of bank lending. Secondly, from the viewpoint of a person's lifetime wealth, the change of property prices will lead to a significant change in the demand for lending. This change can thus smooth one's consumption through one's whole life cycle. Thirdly, property prices can affect not only the banks own assets but also the value of bank lending pledged by the property. That is to say, property prices influence lending willingness and the risk taking the capacity of banks. Alternatively, bank lending can influence the property prices through liquidity effects. Hofmann(2003) declares that, firstly, the property price is decided by the future discounted returns on property. Secondly, if the availability of credit increases, the interest rate will be reduced and the current and future expected economic activity will be stimulated. Consequently, due to a lower discount factor and higher expected returns on the property, property prices may increase. Also, it is well known that property is actually a durable good and its short-term supply is fixed. The higher property prices are impacted by the increase of bank loans demand, due to temporarily fixed supply and construct inertia. In another paper, Brissimis and Vlassopoulos (2009) analyze the causality relationship depending on whether it is long-run or short-run and find that it goes both directions in the short-run, nevertheless, there is no causality link between house prices and bank loans in the long run. More recently, Flannery and Lin (2015) provide the theories which suggest the direction could go in both directions. It argues that if credit supply increase supported by financial intermediaries, cheaper and abundant mortgages will appear and therefore make property prices raise. Accordingly, Flannery and Lin (2015) believes that there are two reasons for explaining the idea that higher property prices may boost further lending. Firstly, higher property prices can increase the borrower's collateral value, thereby increasing borrowing capacity. It is called the collateral channel or the credit demand channel. Secondly, as the value of collateral increases, the bank will provide more loans because of larger capacity, and the risk of existing bank loans secured by real estate is getting smaller. This process is named as bank balance sheet channel or called the credit supply channel.

While the above studies have investigated the bidirectional relationship between property price and bank credit, Gerlach and Peng (2005), Board, Ramcharan, and Crowe (2012), Arestis and González (2013) and Flannery and Lin (2015) provide empirical evidence that house prices have a positive impact on bank lending which is based on a vector autoregressive model with multivariable including bank lending, house prices, GDP and interest rate. Gerlach and Peng (2005) conducted the causal relationship analysis between long-term property prices and bank credit in Hong Kong. It shows that house prices can determine bank credit, but in turn, it fails, giving the methodology of the error-correction model. In another paper, Board, Ramcharan, and Crowe (2012) using data from a peer to peer lending website, which is a credit market on the internet and also regarded as a platform for both creditors and borrowers so as to supply unsecured consumer loans. The empirical results refer that the supply of credit is largely impacted by the fluctuations of the house price. Arestis and González (2013) they revisit the important macroeconomic variable bank credit and endogenous it by way of a sample of 15 Organization for Economic Cooperation and Development (OECD) economies and using cointegration technique during the year from 1970 to 2011. The conclusion is that bank credit is driven by residential investment, house prices and disposable income and other factors including share prices and private demand both have a positive correlation on bank credit. It also declares that the determination of demand for credit is fueled by which can determine the affordability of housing, such as prices and incomes. Flannery and Lin (2015) estimate the impact of house prices on bank lending, financing, and credit supply by exploiting the cross-sectional variation in the change of house prices across major USMSAs (Metropolitan Statistical Areas of the United States). In order to find the causal relationship, it relies on the cross-sectional difference in real estate cycles because of natural geographical constraints. They show that housing booms have a large positive impact on the growth of both real estate credit and commercial and industrial (C&I) loans and credit which beyond the impact caused by local economic conditions. In addition, in order to decompose the lending growth and make it into two parts, namely credit supply shocks and credit demand shocks, it analyses bank origination of small business loans at the county level. Their findings suggest that house price appreciation has a positive causal effect on bank credit supply.

Numerous empirical studies support such causality link from bank lending to property prices includes studies of Collyns, C., & Senhadji, A., (2002), Koh et al. (2005), Liang and Cao (2007), Goodin (2008) ,Burdekin and Tao (2014), Ibrahim and Law (2014) and Huang, Leung, and Qu (2015). For the case of four Eastern Asian economies including Thailand, Korea, Singapore, and Hong Kong, Collyns, C., & Senhadji, A., (2001) evaluates a simultaneous causal relationship between bank credit growth and the changes in property prices, and the direction goes from bank credit growth to property price changes. Besides, it further implying that bank credit is one of the remarkable reasons that led to housing bubbles before the East Asian Financial Crisis in 1997. Koh et al. (2005) investigate the increase and collapse of property prices in the Asian real estate in the 1990s and it refers that inflated property prices were caused by the underpricing of the put option imbedded in non-recourse mortgage loans of financial intermediaries. Liang and Cao (2007) finds that under a high dimensional autoregressive distributed lag (ARDL) model, the direction of causality relationship running from bank lending, the interest rate, and GDP to property prices. It also declares that the process is conducted interactively through the error correction term. Besides, it implies that macroeconomic factors such as GDP and income may also contribute to the effect of bank loans on house prices. According to Liang and Cao (2007), empirical research on emerging market economies has often found that there is a one-way causal relationship from bank loans to property prices. In addition, it declares that macroeconomic factors and policy inclination can be seen as the most evident explanation account for the causality relationship goes from bank credit to property prices. Furthermore, Oikarinen (2009) employs time series econometrics and provides valuable insights about intensity link between property prices and bank lending. Accordingly, the results denote that the deregulation of the bank lending in financial markets appears to play an important role in shaping the dynamic interaction between property prices and bank credit. Most recently, Burdekin and Tao (2014) declares in their paper that there is a significant causality running from two ratios, new loans/industrial production ratio and the M2/industrial production ratio, to the growth of property price. Using data from 1999 to 2011 in China, it investigates possible relations between property prices, stock prices, lending activity and inflation based on both multivariate vector autoregressive (VAR) analysis and bivariate causality. In addition, Ibrahim and Law (2014) investigates the case of Malaysia, mainly focus on the long-term behavior of property prices and its dynamic interaction with bank lending, the actual output, and the interest rate. Besides, the empirical analysis is carried out in a multivariate setting, with the exception of two main variables including the actual output, and the interest rate and cointegration techniques, Granger causality and generalized impulse response functions have been used during the estimation period. Aside from aggregate property prices, several house price sub-indices, such as the semidetached house price index and the detached house price index, which had been included in a separate VAR framework in the study. In general, this paper note that the significant relationship between house prices and bank credit and their variation both have a significant impact on short-term output, and bank lending is considered to be actively pursued in a long-term equation of property prices. The results indicate that because of downward adjustments of property prices and bank lending, there exists a positive deviation of property prices from their long-term value based on a VECM. Huang, Leung, and Qu (2015) conducts multi-step estimation based on China 's urban - level data which includes 29 cities, most of which are the capital cities all over the country covered the period from 1999 to 2012. Also, social diversity geological and environmental can be regarded as the control variable in the paper. As said, if other things are the same, people prefer housing in places where higher quality life is provided. Because a house is an immobile and durable good, so the local amenities and location matter. The empirical results of the paper suggest that property prices have an import effect on bank lending before, but bank loans have a significant effect in increasing property prices after the great recession. In particular, bank loans do not seem to have any important effect on property prices before the 2008 financial crisis. Except bank lending, it also declares that local facilities such as health care, climate, green covered area, higher education are also capitalized into property prices. In addition, the impact of facilities is definitely not inferior to bank loans.

So far, a number of empirical studies have studied this issue. Still, the direction of causality relationship between property prices and bank lending is mixed. All in all, some researchers pursue that bank lending is the result that caused by the property prices, others argue that bank lending is the reason the can affect property prices. Furthermore, the bidirectional causality relationship between property prices and bank lending is supported by a few studies. Besides, in the paper of Goodhart and Hofmann (2008), it addresses that there is a multi-directional interaction among the variables of private credit, property prices, and the macro-economy. There is no conclusive answer from all researchers, however, leave a spot for further research.

3 The Dataset

3.1 Description of the data

The empirical analysis is based on quarterly time series data for China and the US spanning the period 2001Q1 till 2016Q4 and 2001Q1 till 2016Q2 respectively. The economic variables used in this work comprise property prices (PP), bank lending (BL), GDP, CPI and interest rate (R). The set of data series used for China is all collected from China Economic Information Network ("CEInet" in short). The set of data series used for the US is all extracted from the ST. Louis FRED database.

Property price (PP): Because there is no unified standard of property price index for China for the sample period, commercial housing sales, and commercial housing sales area on a monthly basis were collected from 2001 to 2016. The nominal property price for China is calculated dividing commercial housing sales by commercial housing sales area. The next step is to divide the nominal values by consumer price index (CPI) with 2001Q1 as the base.

For U.S., the set of data series used is an index of real residential property prices. Real residential property prices index is on a quarterly basis from 2001Q1 to 2016Q2.In order to compare with the data from China, the quarterly value of 2001Q1 is taken as 100.

The fluctuation of property prices indicate the development of real estate over the sample period and serve as the key variable in the analysis.

Bank lending (BL): One of the most fundamental variables in this analysis is bank lending. For China, nominal bank lending corresponds to nominal total loans and its real value is also derived by dividing nominal values with consumer price index (CPI) with 2001Q1 as the base.

For the U.S., bank lending indicates loans to households and nonprofit organization. Real loans of the U.S are obtained dividing nominal values by the consumer price index (CPI) with 2001Q1 as the base.

For China, nominal total bank lending is utilized rather than property-related bank lending, which is justified by the fact that housing construction in the corporate sector and the real estate investment can be the alternative lending channels for banks or other financial institutions. Moreover, according to Liang and Cao (2007), there is anecdotal that some other loans belong to the household sectors and corporate was effectively used for real estate investment.

Gross domestic product (GDP): For China, the nominal gross domestic product was collected at CEInet on a quarterly level from 2001Q1 to 2016Q4. The real GDP was then derived dividing nominal values by consumer prices index (CPI) with 2001Q1 as the base.

For U.S., the real gross domestic product quarterly time series data was retrieved from FRED database and then 2001Q1 was made the base.

Consumer prices index CPI: Because of monetary policies and other inflationary mechanisms, the increase in the general prices needs to be controlled by using the Consumer prices index. Besides, Leung, Chow, Yiu &Tam (2010) declares that, in China, the second largest contributor that can boost the growth of inflation is the real estate during the period from 2002 to 2004, which further implies that CPI is a vital indicator when studying the issue of property prices. Therefore, this is the measure of inflation chosen to be included in this study.

The main role of CPI is to be used to get other variables real values. For both countries, the time series data of CPI are collected on a monthly level. Firstly, the Growth multiplier of CPI can derive by per month compared to last month$M_{a,n,x}$ (a stands for the year from 2001-2016, n denotes for quarter 1,2,3,4, x is the number of months per quarter, 1, 2, 3). Therefore, growth multiple of CPI per quarter compared to the previous quarter can get through the product of the growth multiplier of the three months of the quarter, $S_{a,n} = M_{a,n,1} \times M_{a,n,2} \times M_{a,n,3}$ (a stands for the year from 2001-2016, n denotes for quarter 1, 2, 3, 4). Then set the value for the first quarter of 2001,$K_{2001,1} = 100$ so the nth quarter value of the nth year is $K_{a,n} = 100 \times \prod_{k=2001,2}^{a,n} S_k$ (a stands for year from 2001-2016, n denotes for quarter 1, 2, 3, 4).

Interest rate (R): The interest rate has a significant impact on the ability of individuals to buy residential properties by increasing or decreasing the opportunity cost of mortgage capital. In fact, the interest rate is a policy instrument which is determined by the central bank of China.

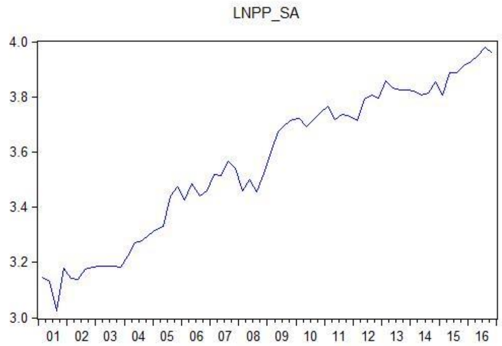
The interest rate of China denotes lending rate in one year in percentage on a monthly level. For the U.S., the interest rate is bank prime loan rate also in percentage on a monthly level. Due to the lack of some effective weighting conditions, the average method was used to get quarterly interest rate for both countries.

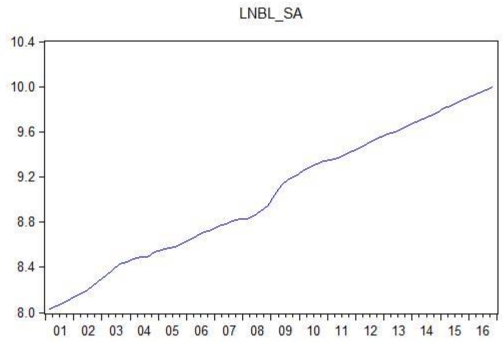
3.2 Descriptive Statistics

The number of observations used in Chinese series is 64 and 62 for the U.S.

For China, except for the interest rate (R), all other data were seasonally adjusted and then transformed into natural logs. While for the U.S, except for consumer prices index (CPI) and gross domestic product (GDP), all other data needed to be seasonally adjusted. In addition, except for the interest rate (R), a natural logarithm transformation has been computed to all data so as to deal with asymmetry and nonnormality.

The data are analyzed using the econometric software EVIEWS 9.





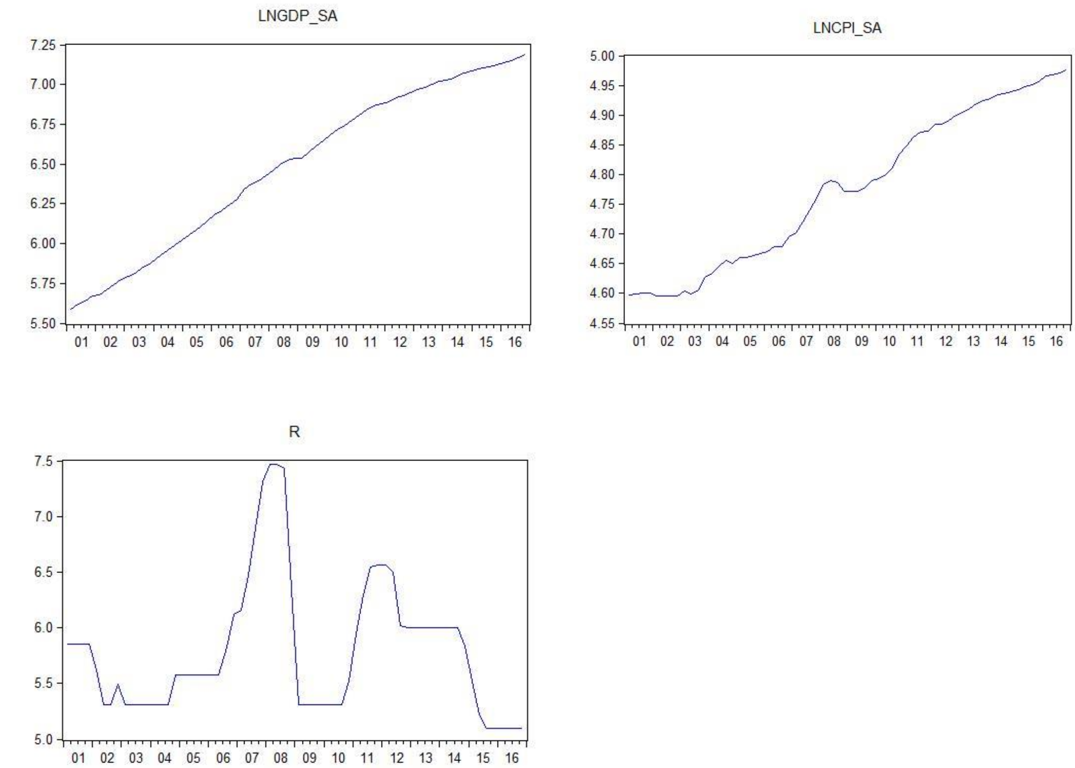
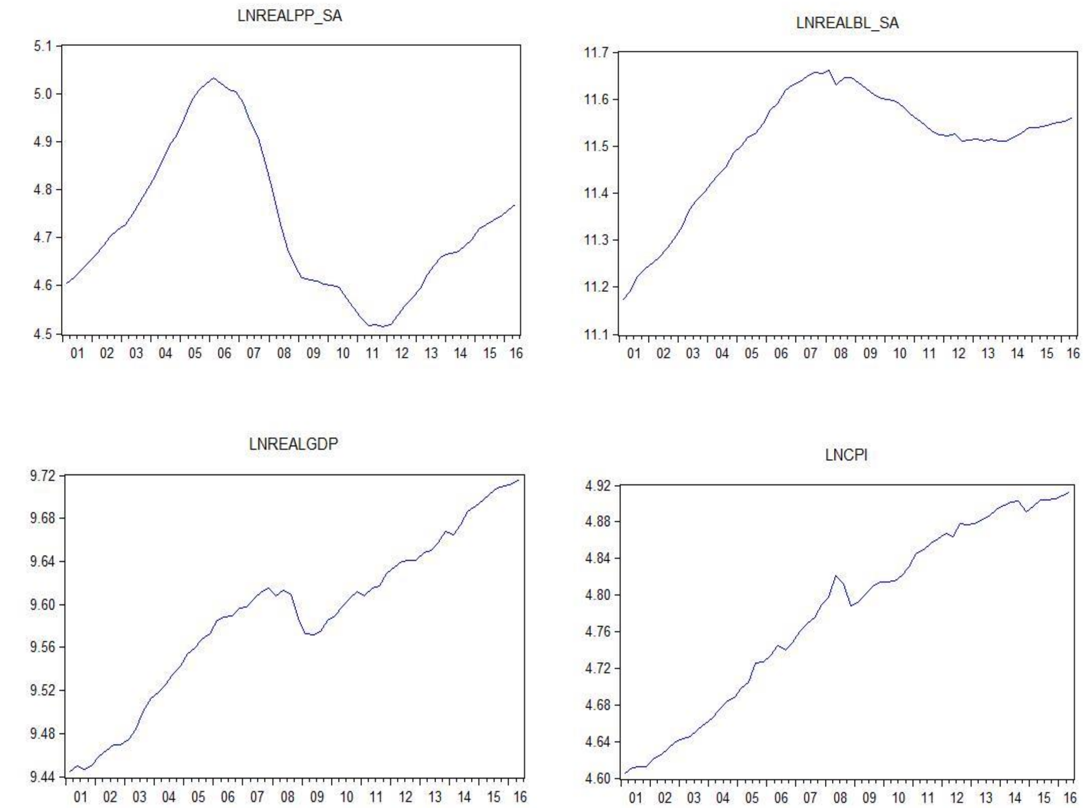


Figure 1. Real property prices (PP), real total loans (BL), real GDP, real CPI and real interest rate ® for China.



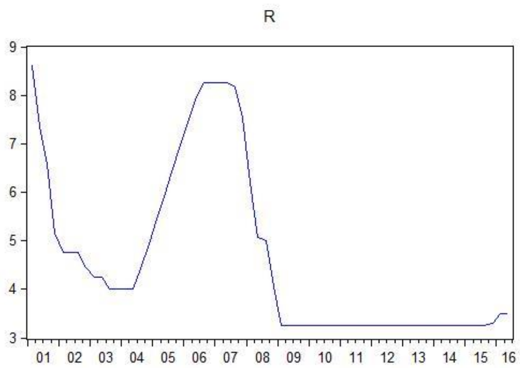


Figure 2. Real property prices (PP), real loans (BL), real GDP, real CPI and real interest rate ® for the US.

As we can see above, for China, there is same upward linear-trend among PP, BL, GDP and CPI and the growth of PP and BL appear to be highly consistent. Besides, property prices have a large fluctuation in the ascending phase. However, due to the impact of the 2008 financial crisis, property prices and bank lending are both subject to a major fluctuation, decreasing in 2008 and then increasing after the crisis in 2009. Moreover, the impact of the crisis on CPI is opposite to that on PP and BL, while GDP is not affected much. The last figure presents the interest rate, which is also an instrument of government monetary policy. There is no strong trend related to it, increasing in 2007 and decreasing in 2008. Actually, it is controlled by the government based on the current economic situation, for example, when the economy grew steadily, the government adopted a sound policy consisting of prudent monetary policy but if there is a special situation that deserves a particular intervention, the government's strategy will change greatly.

For the U.S., the growth trend of PP and BL are consistent. Both increased from 2001 to 2006 and from 2012 to 2016 and decrease in the period comprised between 2007 and 2011. Besides, GDP and CPI have the same growth trend on the figure. The 2008 financial crisis was also responsible for these variables fluctuations. In addition, the interest rate is pretty high before 2008 and since then stays low so as to deal with the economic recession that resulted from the financial crisis in 2008. Also, GDP, CPI, and PP are shown at a lower stage in 2008 which coincides with the fluctuation change of the interest rate.

Figures 3 to 6 present additional information for these variables for China while Figures 7 to 10 present information for the US variables.

The Jarque-Bera test illustrates the normality of the series. The null hypothesis is that the observations are normally distributed, therefore, if the probability value is larger than the value of 5% significance level, the null hypothesis (H0) cannot be rejected. In addition, the value of Skewness and Kurtosis test the distribution of the time series data. If the value of Skewness is larger than 0, the time series shows right-skewed distribution but if the distribution is left-skewed the value of Skewness will be smaller than 0. When the value of Skewness is equal to 0, the time series is normally distributed. Furthermore, if the value of Kurtosis is lower than 3, the time series has a platykurtic distribution.

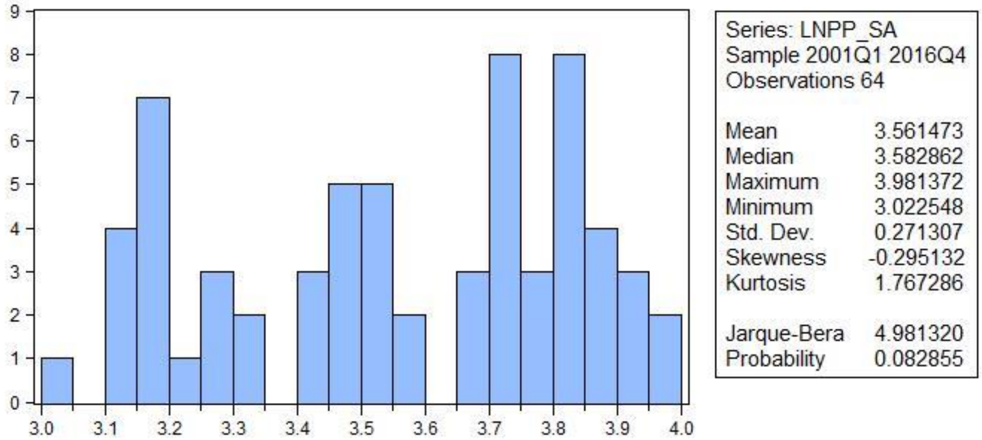


Figure 3. Descriptive statistics of the property price variable, China

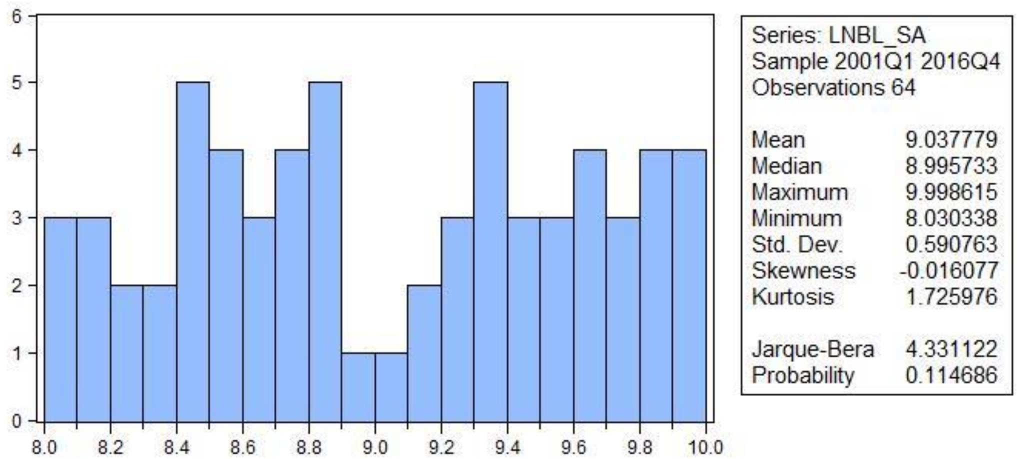


Figure 4. Descriptive statistics of the bank lending (total loans) variable, China.

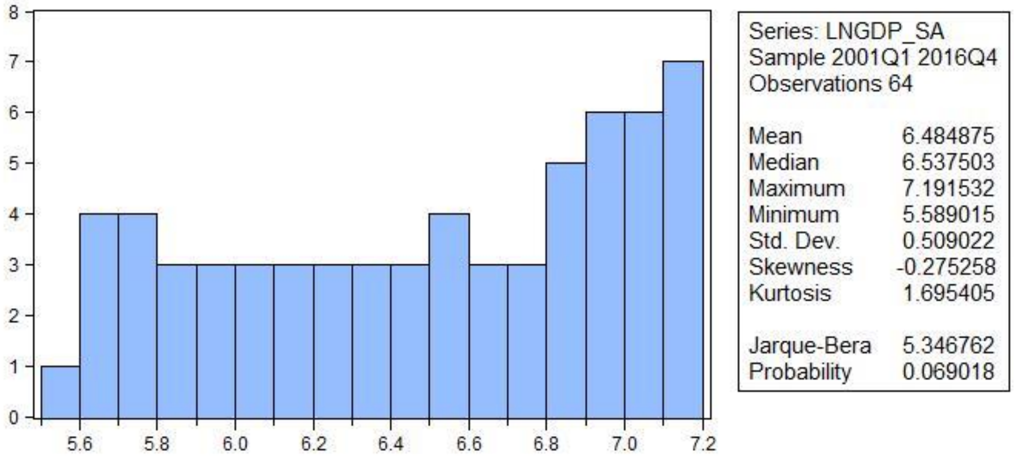


Figure 5. Descriptive statistics of the GDP variable, China.

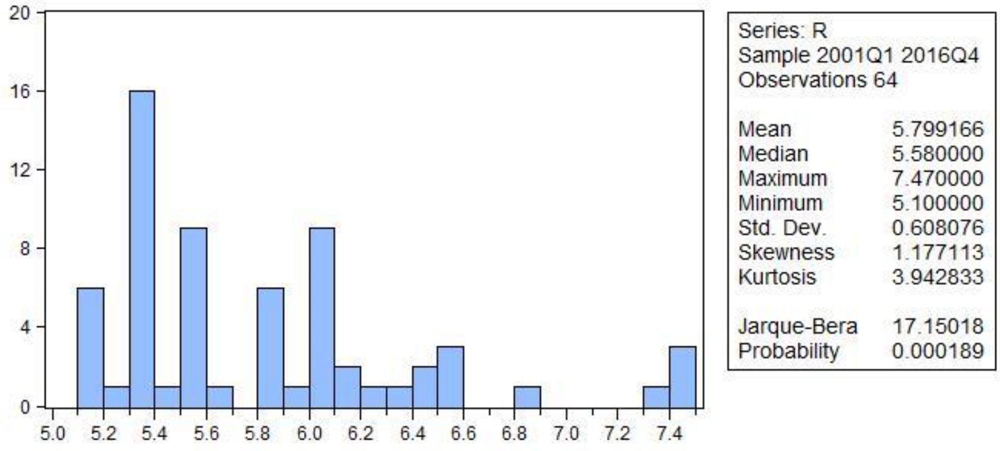


Figure 6. Descriptive statistics of the interest rate ® variable, China.

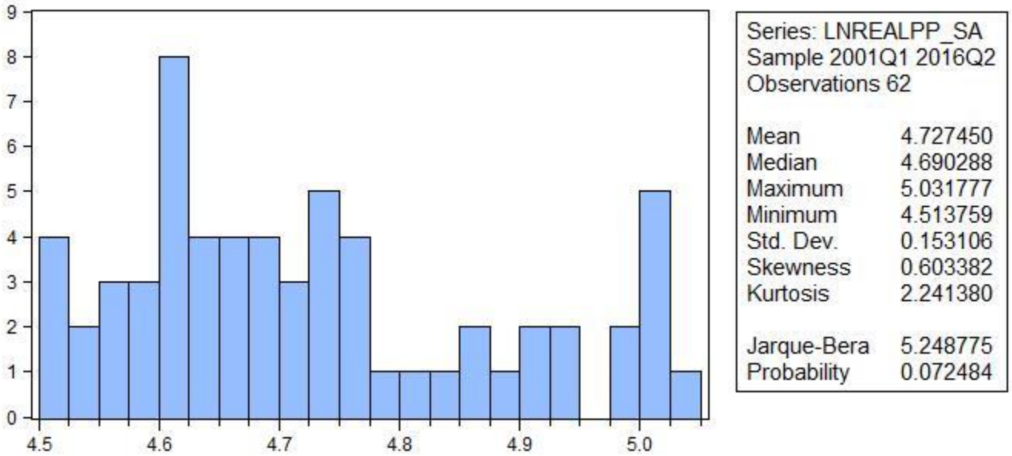


Figure 7. Descriptive statistics of the property price variable, US.

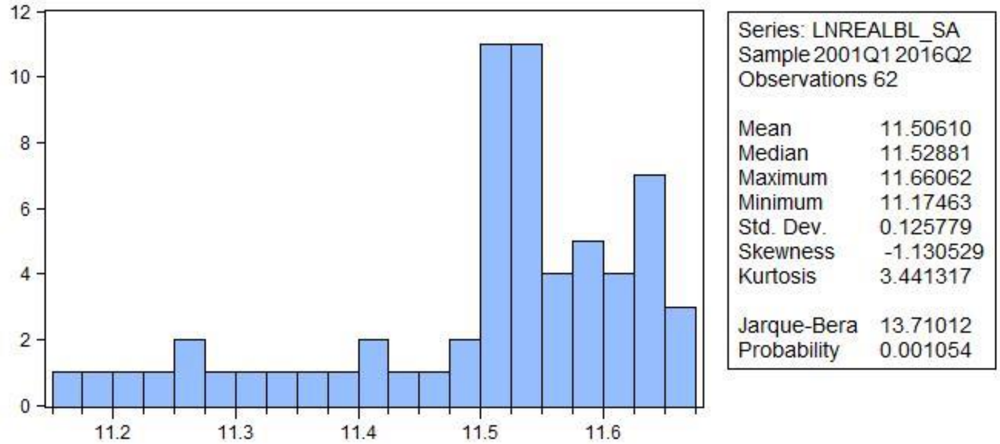


Figure 8. Descriptive statistics of the bank lending variable, US.

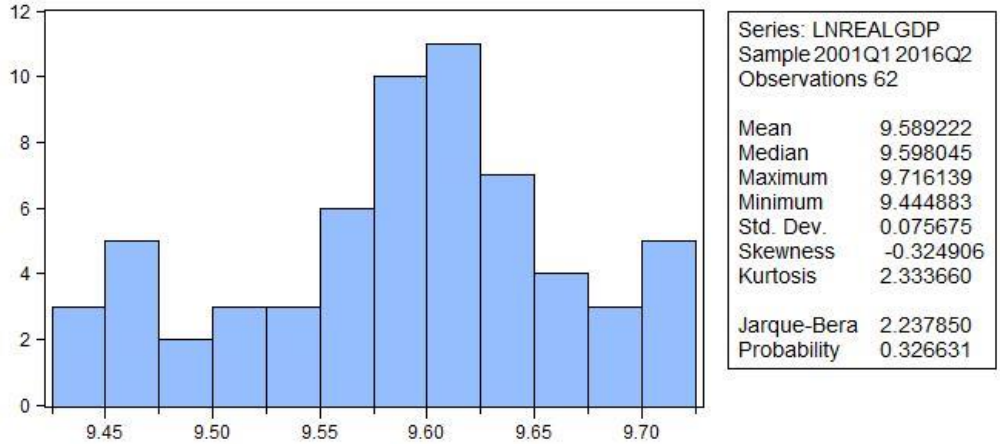


Figure 9. Descriptive statistics of the GDP variable, US.

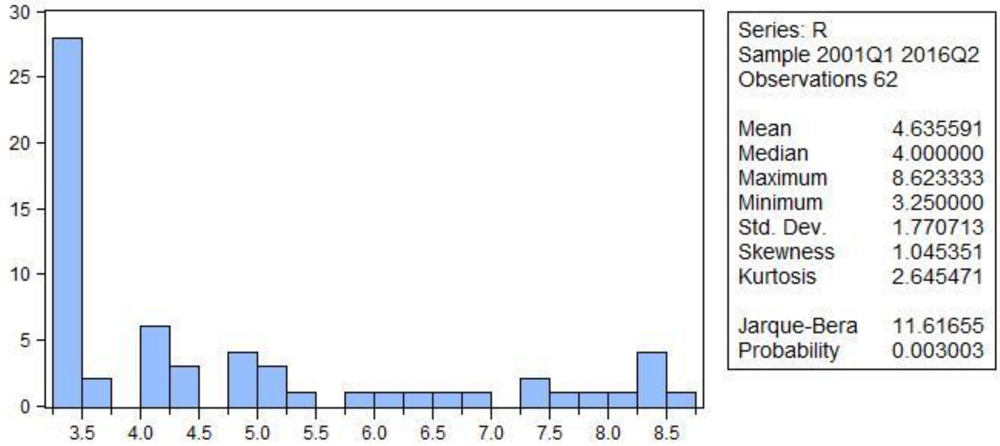


Figure 10. Descriptive statistics of the interest rate (R) variable, US.

With respect to Chinese variables, except for the interest rate, all variables are normally distributed as can be seen from the results from the Jarque-Bera test.

Secondly, the value of Skewness of property prices, bank lending and GDP is smaller than 0, therefore the time series of those variables are left-skewed distributed. However, the value of Skewness of the interest rate is 1.177 indicating that this variable is a right-skewed distribution.

Thirdly, the variables of property prices, bank lending and GDP have a platykurtic distribution, all reporting values of Kurtosis smaller than 3. The value of Kurtosis of the interest rate is 3.94 indicating that this variable is not a platykurtic distribution.

From Figures 7 to 10 that convey descriptive statistics of each variable for the U.S it is possible to observe from the value of the Jarque-Bera test that both property prices and GDP are normally distributed. Because the value of the Jarque-Bera test of bank lending and the interest rate are respectively 0.001 and 0.003, which indicates that the two variables are not normally distributed.

Secondly, from the value of Skewness of property prices and interest rate, these two variables are right-skewed distribution. Bank lending and GDP are left-skewed distributions.

Lastly, except bank lending of which the value of Kurtosis is larger than 3, the value of Kurtosis of property prices, GDP, and interest rate are all smaller than 3 which means property prices, GDP, and interest rate have a platykurtic distribution. Table A. Summarizes the results for the descriptive statistic of each variable for both China and the U.S.

	China			U.S.		
Variables	Skewed distribution	Platykurtic distribution	Normally distributed	Skewed distribution	Platykurtic distribution	Normally distributed
PP	Left	Yes	Yes	Right	Yes	Yes
BL	Left	Yes	Yes	Left	No	No
GDP	Left	Yes	Yes	Left	Yes	Yes
R	Right	No	No	Right	Yes	No

Table A. The conclusion of the descriptive statistic of each variable for both China and the U.S.

4. Methodology

4.1 Unit root test

In fact, the majority of time series macroeconomic data are trended and non-stationary. When working with time series data, the first step is to check the series behavior and draw some conclusions on stationarity. If the time series is not adjusted to non-stationary, the test results of all the classical regression analysis can’t be considered as valid. Moreover, the impact on the stabilization time series must be temporary, and over time because the series returns to its long-term average, so the effects of the impact will be gone. In addition, there are permanent components in non-stationary time series, so the time plays an important role in the mean or variance of the non-stationary time series. Thus, the test results of the regression of non-stationary sequences may be meaningless and may lead to spurious regression.

In general, non-stationary time series may need to undergo multiple differentiation before it becomes stationary. In other words, a series that can be considered as stationary after d differences is called the integral of d order. In addition, another essential information is that, the number of unit roots equal to the number of differenced times of the series and the order of integration of the time series. The current analysis uses two typical tests, which are the Augmented Dickey-Fuller (ADF test) and the Phillips-Perron (PP test). They can be used to check the stationarity of the time series. Besides, the ADF test is based on a parametric autoregressive structure which can catch serial correlation, while PP test is due to the non-parametric corrected intensity of the long-term variance on account of the first order difference of the time series.

Additionally, PP test and ADF test have the same null hypotheses, being:

H0: there is a unit root (the time series is non-stationary)

H1: there is no unit root for the time series (the time series is stationary)

If the absolute value of ADF is higher than the absolute value on a 1%, 5% or 10% significant level, the H0 is rejected on that significant level. Therefore, the time series is stationary.

4.2 VAR model

When estimating the economic model, there may exist simultaneous problems if it is not possible to clearly identify which variables are exogenous or endogenous or even considered to be predetermined variables. However, according to Hall & Asterious(2011), it refers that Sims (1980) strongly criticized this distinction between endogenous and exogenous variables. Sims believes that all the variables should be treated as the same if there exists simultaneity among the variables. In other words, all the variables should be treated as endogenous. This prompted the development of the Vector Auto-Regression (VAR) model.

Actually, the VAR model t is very simple since there is no need to concerned about which variables are exogenous or endogenous. Besides, the estimate is also very simple, because each equation of the model can be estimated by the usual OLS method separately. Nevertheless, the VAR model has some shortcomings. Firstly, it is not in view of any economic theory, in other words, there is no limit or restrictions to the estimated parameters. Therefore, some coefficients of the model might appear to be insignificant. In order to make the model have an underlying consistent theory, it is possible to ignore those coefficients. As a result, for the VAR model, statistical inference is normally carried out using Granger causality test which is presented in section 4.4.

In general, VAR model is treated as an econometric method which can be used to model multivariate time series and it is comprised by a particular system of multiple auto-regression equations. The main idea is to depict a liner function which is relied on the past values of a set of the endogenous variables over the same sampling period. The variables of the model are collected in a k × 1 vector X_t, and X_{ti} can be seen as the variable with the observation of time t and ith element. Thus, a VAR of pth order or with p lags can be regarded as VAR (p):

$$X_t = \beta_1 X_{t-1} + \cdots + \beta_k X_{t-k} + \mu + \delta_\tau + \varepsilon_t \qquad (1)$$

Here, X is a collected vector of all endogenous variables including the log of real BL, PP, R and GDP,

t stand for a deterministic time trend

μ denote a collected vector of constants.

ε denote a collected vector of white noise error terms.

4.3 Cointegration and VECM

4.3.1 Cointegration

As said, owing to spurious regressions, trended time series may cause significant problems. One of the solutions is to continuously difference the series until the trended time series is stationary and then use regression analysis with the stationary time series which is the condition of establishing a VAR model.

However, this solution is not ideal. On the one hand, for instance, if the model has already been correctly specified a relationship between X and Y and the differences of both variables, the error is also differenced implicitly during the regression. As a consequence, it would lead to an irreversible moving average error process and the irreversible moving average error process will also cause severe difficulties during the estimation. On the other hand, after differences, for example, the solution for Y is not unique without knowing the past values of X and Y. Therefore it will not be possible to get a unique long-run solution from the model now.

Cointegration then becomes a non-substitutable requirement for any economic model that can use non-stationary time series. Accordingly, Engle and Granger (1987) give the formal definition of cointegration: if Z_t stand for a n×1 vector of series $Z_{1t}, Z_{2t}, Z_{3t}, \ldots, Z_{nt}$ and if

(a) each Z_{it} is $I(d)$, which means that individually series will have to be integrated of the same order;

(b) There is n × 1 collected vector of β, and if $Z_t'\beta \sim \mathrm{I}(\mathrm{d}-\mathrm{b})$ then $Z_t \sim CI(d,b)$. In other words, Zt denotes an inferior order of integration and the following requirements should be satisfied such that d≥b≥0 and β≠0. Therefore, the n×1 collected vector β is called as the cointegrating vector and the variables are cointegrated of order (d, b).

Besides, for n number of variables, it can exist at most n – 1 cointegrating vector.

4.3.2 VECM and the Johansen Method

The Johansen test is based on a vector autoregressive (VAR) system and it is used when there is more than one cointegrating vector. As stated before, a VECM is an ideal model for deepening estimation when compared with the VAR model.

Firstly, the estimation framework of VECM is based on an unrestricted pth-order VAR model presented in equation (1).

If X_t is a cointegrated procedure, then the above representation can be expressed as a VECM:

$$\Delta \mathrm{X_t} = \Gamma_1 \Delta \mathrm{X_{t-1}} + \cdots + \Gamma_{k-1}\Delta\mathrm{X_{t-k-1}} + \Pi\mathrm{X_{t-1}} + \mu \qquad (2)$$

Where Δ denote first-difference operator, $\Gamma_i = (\mathrm{I} - \mathrm{A}_1 - \mathrm{A}_2 - \cdots - \mathrm{A}_k), \Pi = -(\mathrm{I} - \mathrm{A}_1 - \mathrm{A}_2 - \cdots - \mathrm{A}_k)$, here I denotes a $\mathrm{n} \times \mathrm{n}$ identity matrix. Also, the information of the long $-$

term relationship is included in the Π matrix. Besides, the VECM is cointegrated of order r when the rank of matrix Π is equivalent to the order r. Furthermore, if the rank r equals p, which means matrix Π is full rank, therefore X_t are stationary. However, ΔX_t can be stationary when the rank r is equal to zero, thus, it is possible to conclude that all linear combinations of X_t are integrated of order one I (1) and the number of non-zero eigenvalues of matrixΠ can determine the rank.

Gimeno and Martinez-Carrascal (2006) argue that Johansen (1991) defined tests on the rank of Π by way of a general Likelihood Ratio test. Accordingly, it declares that the null hypothesis is the cointegration rank is at most r (H(r)). In addition, Johansen suggested another two hypotheses. The first hypotheses (H1) refers that Π is full rank (r=p) and the Likelihood Ratio test statistic is presented below which is also known as the trace statistic:

$$T_{trace} = -2\ln\left(Q; H_{(r)}\middle|H_1\right) = -T\sum_{i=r+1}^{p}\ln(1-\lambda_i) \qquad (3)$$

Here, λi denote the estimated eigenvalues of matrixΠ.

The second alternative hypotheses imply that the rank is equivalent to $\mathrm{r}+1(H_{(r+1)})$, thus the maximum Eigenvalue test can be shown as follows:

$$T_{\lambda max} = -2\ln\left(Q; H_{(r)}\middle|H_{(r+1)}\right) = -T ln(1-\lambda_{r+1}) \qquad (4)$$

In addition, it is likely to decompose Π= αβ′ if the number of cointegration relationship (r) has been selected. Notably, α in the matrix Π could imply speed adjustment which can adjust the equilibrium coefficients, while β′ can be the coefficients of the long-run matrix.

For the purpose of finding the number of cointegration relationship, maximum Eigenvalue test, and the trace test are used. Primarily, the null hypothesis of the maximum Eigenvalue test is an alternative hypothesis of r and r + 1 cointegration relationships, while the null hypothesis of the trace test is an alternative hypothesis of r and p cointegrating relations, where r=0,1…p-1 and here p is the number of endogenous variables in the model.

4.4 Granger Causality

According to Hall & Asterious(2011), it shows that there was a relatively simple test which can be used to test causal relationship between the variables developed by Granger (1969) also known as the Granger Causality Test. As said, a variable y_t is said to Granger-cause x_t with the condition of X_t can be expected more accurate by means of past values of the Y_t variable instead of not using these past values. Moreover, all other terms need to be unchanged. In addition, Granger causality test is equivalent to strong exogeneity in case the variables are cointegrated. Actually, the approach of Granger (1969) is based on two stationary series. The main idea is to discover how much the past values of the other series can clarify the current series. Besides, it is probable to observe whether adding lagged values of the past values of series can improve the explanation. In particular, if Y_t is Granger-caused by X_t which infers that Xt helps in the prediction of Y_t, or one can say that coefficients on the lagged X_t's are statically significant. Furthermore, bidirectional causation is possible and frequent.

In the case of two stationary variables of Y_t and X_t, the test involves the estimation of the following VAR models:

$$Y_t = a_1 + \sum\beta_i X_{t-i} + \sum\gamma_j Y_{t-j} + e_{1t} \qquad (5)$$

$$X_t = a_2 + \sum\theta_i X_{t-i} + \sum\delta_j Y_{t-j} + e_{2t} \qquad (6)$$

Here e_{1t}, e_{2t} are the residuals that assumed to be uncorrelated.

t denotes time; i, j both denote the integer value (1, 2…n).

From equation (5) above, only if the lagged coefficients of X terms are statistically different from zero as a group, therefore, X Granger causes Y. In turn, if Y Granger causes X, which means that the lagged coefficients of the Y terms are statistically different from zero as a group in equation (6). Furthermore, if both the lagged coefficients of X terms and Y terms in equation (5) and (6) are statistically different from zero one can say there is two-way causality and if this is not the case, which means if both the lagged coefficients of equation (5) and (6) are not different from zero, one can imply that $X_t$is independent of Y_t.

At last, for application, the null and the alternative hypotheses are as follows:

H0: X_t does not cause Y_t

H1: X_t does cause Y_t

5. Empirical results

According to a four-stage process, the dynamic linkage between bank lending, property prices, interest rate and GDP are analyzed below both in China and the U.S.

5.1 Unit root tests (ADF and PP test)

Tables 1 and 2 in Appendix indicate that, according to unit root test of ADF and PP test, all variables for China including real GDP, real bank lending (BL), real property prices (PP), and real interest rate (R) are trend non-stationary, and significant at 5% level. Besides, Tables 3 and 4 in Appendix show that the first difference of GDP, BL, PP, and R are tested to be stationary.

The test results are summarized in Table B as follows:

	ADF test results		PP test results	
Variables	**Level**	**1st difference**	**Level**	**1st difference**
Real GDP	1.585068(T)	-4.922655(C)*	1.125579(T)	-4.979772(C)*
Real BL	-2.944633(T)	-3.912508(C) *	-2.141728(T)	-3.973687(C) *
Real PP	-3.25855(T)	-10.33184(C) *	-3.313329(T)	-10.42350(C) *
Real R	-3.190944(T)	-4.174060(C) *	-2.234400(T)	-4.327957(C) *

Table B. ADF and PP unit root test results for China

Note 1) T and C indicate whether the test regression includes a time trend and a constant (T), and only a constant(C)

2) * denote significance at the 5% level

Overall, both test results suggest that for China all of the variables are integrated of order one I (1).

Subsequently, tests on the US variables were performed.

Tables 5 and 6 imply that, according to both ADF and PP test, real GDP, real interest rate (R), property prices (PP) and bank lending (BL) are trend non-stationary, significant at 5% level.

Secondly, Tables 7 and 8 show the first difference of real GDP and real interest rate (R) are tested to be stationary using the ADF test, Tables 9 and 10 indicate that the second difference of real property prices (PP) and real bank lending (BL) are tested to be stationary, also using the ADF test. It can, therefore, infer that for ADF test real GDP and real interest rate (R) are integrated of order one, however, real property prices (PP) and real bank lending (BL) are integrated of order two.

Tables 11 and 12 presenting results for the PP test denote that except for real property prices (PP) which are integrated of order two, all other variables including bank lending, GDP, and interest rate are integrated of order one.

The test results to the time series variables of the U.S are summarized in Table C.

	ADF test results		PP test results	
Variables	**Level**	**2nd difference**	**Level**	**2ndt difference**
Real PP	-3.434916 (T)	-6.404185(C) *	-1.746728 (T)	-6.475641 (C) *
Real BL	-2.298545 (T)	-9.078838(C) *	-2.119423 (T)	1st difference -3.741776 (C) *
Variables	**Level**	**1st difference**	**Level**	**1st difference**
Real GDP	-1.896631 (T)	-4.747840(C) *	-1.725854 (T)	-4.737230 (C) *
Real R	-3.474490 (T)	-3.833778(C) *	-2.404179 (T)	-3.736692 (C) *

Table C. ADF and PP unit root test results for the U.S.

Note 1) T and C indicate whether the test regression includes a time trend and a constant (T), and only a constant(C)

2) * denote significance at the 5% level

Since, in general, the ADF test is the most suitable method to test for unit roots when compared with other unit root tests, and especially with the condition that the form of the data-generating process is unknown, thus the analysis will rely much upon on the results of the ADF test.

Therefore, from Table C, for the U.S., real GDP and real interest rate (R) are integrated of order one, I (1), while real property prices (PP) and real bank lending (BL) are integrated of order two, I (2).

5.2 VAR estimation

In order to find the optimal lag length for establishing the VECM later, a VAR model was established.

The goal of this step is to better establish the VECM. Then, a VECM will be estimated in order to analyze what is the dynamic relationship between property prices and bank lending. Furthermore, because the inference is to some extent dependent on the correctness of the selected lag order, the process of choosing the optimal lag p in the VAR model plays a pivotal role. The optimal lag is normally chosen based on two statistic criterion – Akaike (AIC) and Schwarz (SC). Also, the optimal lag of the model is determined according to the principle of minimum AIC value.

VAR Lag Order Selection Criteria
Endogenous variables: D1 D2 D3 D4
Exogenous variables: C
Date: 05/18/17 Time: 13:56
Sample: 2001Q1 2016Q4
Included observations: 58

Lag	LogL	LR	FPE	AIC	SC	HQ
0	461.7911	NA	1.64e-12	-15.78590	-15.64380	-15.73055
1	501.8257	73.16683	7.16e-13	-16.61468	-15.90418*	-16.33793*
2	520.6431	31.79486*	6.56e-13*	-16.71183*	-15.43294	-16.21368
3	532.7640	18.80830	7.65e-13	-16.57807	-14.73078	-15.85851
4	548.0033	21.54525	8.18e-13	-16.55184	-14.13615	-15.61088
5	565.1917	21.93003	8.39e-13	-16.59282	-13.60873	-15.43045

* 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
HQ: Hannan-Quinn information criterion

Table D. Lag Length Criteria of VAR model, China

VAR Lag Order Selection Criteria
Endogenous variables: Y3 Y4 Z1 Z2
Exogenous variables: C
Date: 05/18/17 Time: 14:29
Sample: 2001Q1 2016Q2
Included observations: 55

Lag	LogL	LR	FPE	AIC	SC	HQ
0	534.2079	NA	4.97e-14	-19.28029	-19.13430	-19.22383
1	588.4343	98.59347	1.24e-14	-20.67034	-19.94040*	-20.38806*
2	608.7339	33.95576*	1.07e-14*	-20.82669	-19.51280	-20.31860
3	624.9676	24.79325	1.09e-14	-20.83519*	-18.93734	-20.10127
4	638.8899	19.23810	1.23e-14	-20.75963	-18.27784	-19.79990
5	648.6527	12.07041	1.67e-14	-20.53283	-17.46708	-19.34728

* 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
HQ: Hannan-Quinn information criterion

Table E. Lag Length Criteria of VAR model, U.S.

In Tables D and E, the smallest value of the AIC for China is -16.712 for a corresponding lag length of two (D1 stands for property prices after first difference, D2 denotes Bank lending after first difference, D3 is GDP after first difference and D4 is interest rate also after first difference).For the U.S., the smallest value of AIC indicates that the corresponding lag length is three (Y3 stands for GDP after first order difference , Y4 is interest rate after first difference, Z1 is property prices after second order difference and Z2 is bank lending after second difference).

The next step was to perform diagnostic tests for checking the correlation of the residual series, using the autocorrelation LM test. Because the null hypothesis is that there is no serial correlation, thus, if the probability is larger than 0.05, it is not possible to reject H0, there is no serial correlation in residual series as well.

Tables 13 and 14, show that for China, there is no serial correlation in residual series. Similarly, there is no serial correlation in residual series of the U.S., because the probability with lag 3 is 0.5705.

Therefore, the optimal lag length for China is two and for the U.S. is three.

5.3 Cointegration (Johansen method)

The next step is to detect the number of cointegration relationship by using the Trace test and the maximum Eigenvalue test.

Firstly, as can be seen from Table 15 in Appendix, for China, both the Trace test and the Maximum Eigenvalue test suggest that there is a unique cointegration relationship. In addition, the one that best fits the cointegration equation is the model with no deterministic trend (restricted constant). The results of the trace test and the maximum Eigenvalue Statistic are reported in Table 16 in Appendix. It performs that the null hypothesis of no cointegration vector can be rejected, but the alternative hypothesis of at most one cointegrating vector cannot be rejected. In general, the results indicate that there is indeed a single relationship between bank lending, property prices, interest rate and GDP during the estimation period.

It is possible to normalize the model on real bank lending according to Table 16, so the cointegration equation can be written as follows,

$$\ln BL = \underset{(0.26407)}{0.146919}\ln PP + \underset{(0.14562)}{0.996147}\ln GDP - \underset{(0.01480)}{0.116639}R + \underset{(0.13783)}{3.004137} \quad (7)$$

It is notable that the parameter on property prices for China is 0.1469, which means that bank lending increases 0.1469%, which is insignificant. Besides, the parameter on GDP is almost 1, which indicates that GDP together with bank lending grow proportionally over time.

Likewise, for the U.S, Table 17 points that there is also a single one cointegration relationship. From Table 18, the null hypothesis of at most one cointegrating vector cannot be rejected. Normalizing on bank lending, the cointegration equation is:

$$\ln BL = \underset{(0.21415)}{1.235006}\ln PP + \underset{(0.22918)}{0.065688}\ln GDP + \underset{(0.01644)}{0.008912}R \quad (8)$$

The parameter on property prices is 1.235, implying that if the property prices increase 1% bank lending will increase 1.235%. This coefficient is statistically significant compared with the value of China that was not.

5.4 VECM and Granger causality test

From above analysis, there is a positive relationship between property prices and bank lending in China and the U.S. However, in order to make sure the interaction between the two variables. VECM is further established based on the cointegration relationship and then the Granger-causality test is performed which can make more explicit the fact that the causality direction of property prices and bank lending.

Thus, firstly, the relationship between the variables of China is discussed as follows:

With the condition of all endogenous variables including property prices, bank lending, interest rate and GDP, according to Table 19 in Appendix, the VECM of China can be written as follows,

$$\Delta \mathrm{Yt} = \begin{bmatrix} -0.0895 \\ -0.0943 \\ -0.1273 \\ -1.1136 \end{bmatrix} \mathrm{cointEq1} + \begin{bmatrix} 0.4605 & -0.0208 & -0.3119 & -0.0258 \\ -0.8046 & -0.5665 & 0.2968 & -0.0506 \\ -0.1793 & -0.0386 & -0.0769 & 0.0157 \\ -5.2833 & 0.3152 & -2.7343 & 0.6689 \end{bmatrix} \Delta \mathrm{Yt} - 1 + \cdots \Delta \mathrm{Yt} - 2 + \varepsilon t; \qquad (9)$$

$$\Delta\ \mathrm{Yt} = \begin{bmatrix} D(BL) \\ D(PP) \\ D(GDP) \\ D(R) \end{bmatrix}$$

Here, the cointegration equation of China can be represented as below,

$$BL=0.1469PP+0.9961GDP-0.1166R+3.0041 \qquad (10)$$

As seen above, there is a positive correlation among property prices, bank lending, and GDP. The interest rate is negatively related to other variables in the model.

Given the VECM model, the Granger-Causality test is also carried out, Table 20 in Appendix refers that the lag length of bank lending cannot explain or predict the property prices, while the lag length of property prices can explain or predict bank lending, in other words, in China, the direction of causal relationship is from property prices to bank lending. Besides, the lag length of interest rate itself can explain or predict bank lending. Moreover, the lag length of property prices, interest rate, and GDP can jointly explain or predict bank lending.

Similarly, VECM is also established within the condition of all variables are endogenous for the U.S.

According to Table 21, the VECM of the U.S. can be written as follows,

$$\Delta \mathrm{Yt} = \begin{bmatrix} -1.567244 \\ 1.028918 \\ -0.101900 \\ -26.00534 \end{bmatrix} \mathrm{cointEq1} +$$

$$\begin{bmatrix} -2.56E-06 & -0.959394 & -0.446265 & 0.015489 \\ -0.615778 & -0.430366 & 0.067111 & 0.008229 \\ 0.074703 & -0.042153 & -0.279729 & -0.007935 \\ 14.74012 & -8.832965 & -2.911702 & 0.060024 \end{bmatrix} \Delta \mathrm{Yt}-1+\cdots \Delta \mathrm{Yt}-3+$$

εt; (11)

$$\Delta\ \mathrm{Yt} = \begin{bmatrix} D(Z2) \\ D(Z1) \\ D(Y3) \\ D(Y4) \end{bmatrix}$$

Again, here Z2 is first difference of bank lending, Z1 is first difference of property prices, Y3 stands for the first difference of GDP, and Y4 is first difference of interest rate.

Here, the cointegration equation of the U.S. can be represented as below,

$$BL=0.401428PP+0.184283GDP+0.000482R+0.000969 \qquad (12)$$

As seen above, there is a positive correlation among property prices, bank lending, the interest rate and GDP.

It implies that the lag length of property prices can explain or predict bank lending, the lag length of bank lending can in turn explain or predict the property prices. That is, the direction of causality goes from two ways between bank lending and property prices in the United States. Similarly, the lag length of interest rate can explain or predict bank lending. Besides, the lag length of bank lending, GDP and interest rate can jointly explain or predict property prices. Furthermore, the lag length of interest rate itself can explain or predict bank lending (see Table 22 in Appendix).

6 Concluding remarks

Through the above analysis, there is a one-way Granger causality relationship running from property prices to bank lending in China; however, there is a bidirectional Granger causality linkage between property prices and bank lending in the United States.

The findings of China are twofold. Firstly, quite a number of bank loans often flow into the real estate sector, thus, if there is fluctuation in the property price, the real estate industry will be largely influenced. Secondly, the interest rate is determined by The People' Bank of China (PBOC) as a macro policy instrument. For example, the Chinese government increased the interest rate so as to prevent the rapid growth of property prices from last year. Because of this policy, the advantages of investing in the housing market have disappeared so that the inflows of bank loans related to the real estate decrease. Therefore, the growth rate of property prices slows down. But hopefully, the slowdown in property prices growth will not have a tremendous influence on GDP growth.

Comparing with China, it appears that housing market and the credit market of the U.S. are much more developed. Although the direction of property prices and bank lending can go both ways, the fluctuation of bank lending in the U.S. plays the predominant role and it also has statistical stability over a certain estimation period. In fact, bank lending is a policy, so it has exogenous to some extent. Therefore, it is more easily to find that the growth the property prices could influence bank lending than the other way around.

China's society and economy growth are developing rapidly nowadays. In the future, China will possibly emerge similar results of bank lending (the proportion of bank loans inflows related to the real estate) as the U.S. today. In other words, the causal relationship between property prices and bank lending may be the same. But, the U.S. had experienced a serious subprime crisis during the sample period, and we don't want the future of China to have the same crisis as the U.S. today. The Chinese government should develop more effective policies. Indeed, in China, the expectation plays a crucial role in the real estate nowadays. The terrible thing is that the property price is overestimated and also it is artificially pushed up. No matter what policy the government established, even if it is a macro-bad policy, people also regard it as a favorable policy (because of the government's rigid guarantee and rigid payment), people will rush to purchase housing, then the property prices become even higher. If the property prices decline from a low level, the risk is relatively more controllable; but if it declines from a high level, the risk will be high which will jeopardize the whole bank systems or even the economy. Therefore, the policymaker should well acknowledge that the market will react in advance which would offset the policy effect or even has the opposite influence.

It should be noted that the current analysis is done at the national level. However, China's geographical scale is large, which can cause great diversity for different regional economic. Therefore, the future research work should focus on provincial analysis and give enough attentions on the comparison of urban-rural analysis on this issue.

Appendix

Null Hypothesis: LNGDP_SA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.585068	1.0000
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Null Hypothesis: LNBL_SA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.944633	0.1562
Test critical values:	1% level	-4.113017	
	5% level	-3.483970	
	10% level	-3.170071	

Null Hypothesis: LNPP_SA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.258550	0.0828
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.190944	0.0957
Test critical values:	1% level	-4.113017	
	5% level	-3.483970	
	10% level	-3.170071	

Table 1 ADF test result for GDP, BL, PP, and R in levels, China

Null Hypothesis: LNGDP_SA has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		1.125579	0.9999
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Null Hypothesis: LNBL_SA has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.141728	0.5129
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Null Hypothesis: LNPP_SA has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.313329	0.0735
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.234400	0.4626
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Table 2 PP test result of GDP, BL, PP and R in levels, China

Null Hypothesis: D(LNGDP_SA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.922655	0.0001
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Null Hypothesis: D(LNBL_SA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.912508	0.0034
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Null Hypothesis: D(LNPP_SA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.33184	0.0000
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.174060	0.0015
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Table 3 ADF test result of GDP, BL, PP and R in the 1st difference, China.

Null Hypothesis: D(LNGDP_SA) has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.979772	0.0001
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Null Hypothesis: D(LNBL_SA) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.973687	0.0028
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Null Hypothesis: D(LNPP_SA) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-10.42350	0.0000
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.327957	0.0009
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

Table 4 PP test result of GDP, BL, PP and R in 1st difference, China

Null Hypothesis: LNREALGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.896631	0.6439
Test critical values:	1% level	-4.118444	
	5% level	-3.486509	
	10% level	-3.171541	

Null Hypothesis: LNREALBL_SA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.298545	0.4279
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	

Null Hypothesis: LNREALPP_SA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.434916	0.0563
Test critical values:	1% level	-4.118444	
	5% level	-3.486509	
	10% level	-3.171541	

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.473390	0.0519
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	

Table 5 ADF test result of GDP, BL, PP and R in the levels, U.S.

Null Hypothesis: LNREALGDP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.725854	0.7277
Test critical values:	1% level	-4.115684	
	5% level	-3.485218	
	10% level	-3.170793	

Null Hypothesis: LNREALBL_SA has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.119423	0.5247
Test critical values:	1% level	-4.115684	
	5% level	-3.485218	
	10% level	-3.170793	

Null Hypothesis: LNREALPP_SA has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.746728	0.7181
Test critical values:	1% level	-4.115684	
	5% level	-3.485218	
	10% level	-3.170793	

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.404179	0.3738
Test critical values:	1% level	-4.115684	
	5% level	-3.485218	
	10% level	-3.170793	

Table 6 PP test result of GDP, BL, PP and R in levels, U.S.

Null Hypothesis: D(LNREALGDP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.747840	0.0002
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

Table 7 ADF test result of GDP in the 1st difference, U.S

Null Hypothesis: D(R) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.833778	0.0044
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

Table 8 ADF test result of R in the 1st difference, U.S

Null Hypothesis: D(LNREALPP_SA,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.404185	0.0000
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

Table 9 ADF test result of PP in the 2nd difference, U.S.

Null Hypothesis: D(LNREALBL_SA,2) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.078838	0.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

Table 10 ADF test result of BL in the 2nd difference, U.S.

Null Hypothesis: D(LNREALPP_SA,2) has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.475641	0.0000
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

Table 11 PP test result of PP in the 2nd difference, U.S

Null Hypothesis: D(LNREALBL_SA) has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.741776	0.0057
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

Null Hypothesis: D(LNREALGDP) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.737230	0.0003
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

Null Hypothesis: D(R) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.736692	0.0058
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

Table 12 PP test result of BL, GDP, and R in the 1st difference, U.S

VAR Residual Serial Correlation LM Tes
Null Hypothesis: no serial correlation at l
Date: 05/18/17 Time: 13:59
Sample: 2001Q1 2016Q4
Included observations: 61

Lags	LM-Stat	Prob
1	21.89685	0.1466
2	19.51261	0.2430
3	10.90987	0.8150

Probs from chi-square with 16 df.

Table 13 Autocorrelation LM test, China

VAR Residual Serial Correlation LM Tes
Null Hypothesis: no serial correlation at l
Date: 05/18/17 Time: 14:32
Sample: 2001Q1 2016Q2
Included observations: 57

Lags	LM-Stat	Prob
1	14.18562	0.5849
2	8.740206	0.9237
3	14.37942	0.5705
4	13.95488	0.6021

Probs from chi-square with 16 df.

Table 14 Autocorrelation LM test, U.S

Date: 05/18/17 Time: 14:02
Sample: 2001Q1 2016Q4
Included observations: 61
Series: LNBL_SA LNPP_SA LNGDP_SA R
Lags interval: 1 to 2

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

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	1	1	0	0
Max-Eig	0	1	0	0	0

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

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	540.0270	540.0270	545.7854	545.7854	550.9948
1	552.0746	557.6224	559.5009	559.5648	563.1820
2	559.8212	565.5796	566.1090	568.5768	571.3585
3	561.8536	570.0329	570.4481	572.9195	575.3807
4	562.9311	572.0411	572.0411	575.4712	575.4712
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	-16.65662	-16.65662	-16.71428	-16.71428	-16.75393
1	-16.78933	-16.93844*	-16.90167	-16.87098	-16.89121
2	-16.78102	-16.90425	-16.85603	-16.87137	-16.89700
3	-16.58536	-16.75518	-16.73600	-16.71867	-16.76658
4	-16.35840	-16.52594	-16.52594	-16.50725	-16.50725
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	-15.54928*	-15.54928*	-15.46851	-15.46851	-15.36975
1	-15.40515	-15.51966	-15.37907	-15.31377	-15.23020
2	-15.12001	-15.17403	-15.05660	-15.00273	-14.95915
3	-14.64751	-14.71351	-14.65973	-14.53859	-14.55189
4	-14.14371	-14.17283	-14.17283	-14.01573	-14.01573

Table 15 Johansen cointegration test summary, China

Date: 05/18/17 Time: 14:03
Sample (adjusted): 2001Q4 2016Q4
Included observations: 61 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: LNBL_SA LNPP_SA LNGDP_SA R
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.438363	64.02824	54.07904	0.0050
At most 1	0.229636	28.83740	35.19275	0.2058
At most 2	0.135851	12.92299	20.26184	0.3700
At most 3	0.063721	4.016378	9.164546	0.4097

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.438363	35.19084	28.58808	0.0062
At most 1	0.229636	15.91441	22.29962	0.3044
At most 2	0.135851	8.906614	15.89210	0.4439
At most 3	0.063721	4.016378	9.164546	0.4097

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LNBL_SA	LNPP_SA	LNGDP_SA	R	C
-24.07712	3.537376	23.98435	-2.808328	72.33095
4.983758	31.78591	-22.03617	0.282316	-18.27415
-28.35490	-38.73239	53.47689	-5.610882	80.97770
-9.021421	-2.893488	13.73340	-0.634695	6.905591

Unrestricted Adjustment Coefficients (alpha):

D(LNBL_SA)	0.003718	-0.001694	-0.001160	0.001674
D(LNPP_SA)	0.003916	-0.009702	0.008223	-0.000953
D(LNGDP_SA)	0.005287	-0.000124	-0.000416	-0.001138
D(R)	0.046251	0.081868	0.029328	-0.000689

1 Cointegrating Equation(s): Log likelihood 557.6224

Normalized cointegrating coefficients (standard error in parentheses)

LNBL_SA	LNPP_SA	LNGDP_SA	R	C
1.000000	-0.146919	-0.996147	0.116639	-3.004137
	(0.26407)	(0.14562)	(0.01480)	(0.13783)

Adjustment coefficients (standard error in parentheses)

D(LNBL_SA)	-0.089514
	(0.03061)
D(LNPP_SA)	-0.094277

	(0.10245)				
D(LNGDP_SA)	-0.127300				
	(0.02531)				
D(R)	-1.113585				
	(0.65315)				
2 Cointegrating Equation(s):		Log likelihood	565.5796		
Normalized cointegrating coefficients (standard error in parentheses)					
LNBL_SA	LNPP_SA	LNGDP_SA	R	C	
1.000000	0.000000	-1.073278	0.115288	-3.019057	
		(0.01665)	(0.01306)	(0.13379)	
0.000000	1.000000	-0.524988	-0.009194	-0.101551	
		(0.02024)	(0.01588)	(0.16271)	
Adjustment coefficients (standard error in parentheses)					
D(LNBL_SA)	-0.097954	-0.040679			
	(0.03072)	(0.03996)			
D(LNPP_SA)	-0.142627	-0.294525			
	(0.09926)	(0.12911)			
D(LNGDP_SA)	-0.127920	0.014750			
	(0.02585)	(0.03362)			
D(R)	-0.705575	2.765851			
	(0.60577)	(0.78796)			
3 Cointegrating Equation(s):		Log likelihood	570.0329		
Normalized cointegrating coefficients (standard error in parentheses)					
LNBL_SA	LNPP_SA	LNGDP_SA	R	C	
1.000000	0.000000	0.000000	-0.953174	-6.409225	
			(0.39963)	(2.49432)	
0.000000	1.000000	0.000000	-0.531827	-1.759833	
			(0.20297)	(1.26684)	
0.000000	0.000000	1.000000	-0.995513	-3.158706	
			(0.36749)	(2.29370)	
Adjustment coefficients (standard error in parentheses)					
D(LNBL_SA)	-0.065068	0.004243	0.064465		
	(0.04650)	(0.06224)	(0.07759)		
D(LNPP_SA)	-0.375801	-0.613037	0.747463		
	(0.14534)	(0.19451)	(0.24247)		
D(LNGDP_SA)	-0.116130	0.030855	0.107315		
	(0.03939)	(0.05272)	(0.06572)		
D(R)	-1.537164	1.629912	0.873604		
	(0.91197)	(1.22056)	(1.52150)		

Table 16 Johansen cointegration test, China

Date: 05/18/17 Time: 14:34
Sample: 2001Q1 2016Q2
Included observations: 58
Series: LNREALBL_SA LNREALPP_SA LNREALGDP R
Lags interval: 1 to 3

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

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	4	3	1	2	2
Max-Eig	2	2	1	1	1

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

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	656.7188	656.7188	665.8079	665.8079	668.9720
1	672.7760	673.0438	681.8800	685.7928	688.3873
2	681.8832	686.0566	690.7039	697.9632	700.1655
3	686.0198	693.1481	695.5830	704.2333	706.1609
4	688.3259	696.5314	696.5314	709.0911	709.0911
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	-20.99030	-20.99030	-21.16579	-21.16579	-21.13696
1	-21.26814	-21.24289	-21.44414	-21.54458	-21.53060
2	-21.30632	-21.38126	-21.47255	-21.65390	-21.66088*
3	-21.17310	-21.31545	-21.36493	-21.55977	-21.59176
4	-20.97675	-21.12177	-21.12177	-21.41693	-21.41693
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	-19.28511	-19.28511	-19.31850	-19.31850	-19.14757
1	-19.27875	-19.21797	-19.31265	-19.37756*	-19.25701
2	-19.03273	-19.03662	-19.05686	-19.16716	-19.10309
3	-18.61531	-18.65109	-18.66504	-18.75330	-18.74976
4	-18.13476	-18.13768	-18.13768	-18.29074	-18.29074

Table 17 Johansen cointegration test summary, U.S.

Date: 05/18/17 Time: 14:38
Sample (adjusted): 2002Q1 2016Q2
Included observations: 58 after adjustments
Trend assumption: Linear deterministic trend
Series: LNREALBL_SA LNREALPP_SA LNREALGDP R
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.425475	61.44702	47.85613	0.0016
At most 1	0.262339	29.30279	29.79707	0.0569
At most 2	0.154855	11.65510	15.49471	0.1742
At most 3	0.032174	1.896786	3.841466	0.1684

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.425475	32.14423	27.58434	0.0121
At most 1	0.262339	17.64769	21.13162	0.1436
At most 2	0.154855	9.758312	14.26460	0.2283
At most 3	0.032174	1.896786	3.841466	0.1684

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LNREALBL_SA	LNREALPP_SA	LNREALGDP	R
17.50042	-21.61312	-1.149560	-0.155970
28.86476	-10.52788	-7.144390	0.877911
-12.35408	-6.730439	23.94316	0.965657
4.737690	-12.87382	-12.47151	1.077100

Unrestricted Adjustment Coefficients (alpha):

D(LNREALBL_	-0.002260	-0.003309	8.74E-05	-0.000121
D(LNREALPP_	0.002972	-0.002265	-0.000727	-0.000592
D(LNREALGDP	0.000473	-0.000292	-0.000845	0.000641
D(R)	-0.025549	0.003834	-0.064593	-0.004044

1 Cointegrating Equation(s): Log likelihood 681.8800

Normalized cointegrating coefficients (standard error in parentheses)

LNREALBL_SA	LNREALPP_SA	LNREALGDP	R
1.000000	-1.235006	-0.065688	-0.008912
	(0.21415)	(0.22918)	(0.01644)

Adjustment coefficients (standard error in parentheses)

D(LNREALBL_	-0.039546
	(0.01849)
D(LNREALPP_	0.052009

	(0.01785)		
D(LNREALGDP	0.008273		
	(0.01120)		
D(R)	-0.447122		
	(0.44453)		
2 Cointegrating Equation(s):		Log likelihood	690.7039
Normalized cointegrating coefficients (standard error in parentheses)			
LNREALBL_SA	LNREALPP_SA	LNREALGDP	R
1.000000	0.000000	-0.323715	0.046897
		(0.27620)	(0.01839)
0.000000	1.000000	-0.208928	0.045189
		(0.32180)	(0.02143)
Adjustment coefficients (standard error in parentheses)			
D(LNREALBL_	-0.135053	0.083674	
	(0.03145)	(0.02240)	
D(LNREALPP_	-0.013369	-0.040386	
	(0.03244)	(0.02310)	
D(LNREALGDP	-0.000157	-0.007142	
	(0.02155)	(0.01535)	
D(R)	-0.336467	0.511839	
	(0.85720)	(0.61050)	
3 Cointegrating Equation(s):		Log likelihood	695.5830
Normalized cointegrating coefficients (standard error in parentheses)			
LNREALBL_SA	LNREALPP_SA	LNREALGDP	R
1.000000	0.000000	0.000000	0.079187
			(0.02591)
0.000000	1.000000	0.000000	0.066030
			(0.02578)
0.000000	0.000000	1.000000	0.099751
			(0.03278)
Adjustment coefficients (standard error in parentheses)			
D(LNREALBL_	-0.136134	0.083085	0.028331
	(0.03348)	(0.02325)	(0.02330)
D(LNREALPP_	-0.004390	-0.035494	-0.004637
	(0.03432)	(0.02384)	(0.02388)
D(LNREALGDP	0.010285	-0.001454	-0.018694
	(0.02249)	(0.01562)	(0.01565)
D(R)	0.461524	0.946581	-1.544587
	(0.84303)	(0.58551)	(0.58663)

Table 18 Johansen cointegration test, U.S.

Vector Error Correction Estimates
Date: 05/18/17 Time: 14:15
Sample (adjusted): 2001Q4 2016Q4
Included observations: 61 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LNBL_SA(-1)	1.000000
LNPP_SA(-1)	-0.146919 (0.26407) [-0.55635]
LNGDP_SA(-1)	-0.996147 (0.14562) [-6.84089]
R(-1)	0.116639 (0.01480) [7.87972]
C	-3.004137 (0.13783) [-21.7964]

Error Correction:	D(LNBL_SA)	D(LNPP_SA)	D(LNGDP_SA)	D(R)
CointEq1	-0.089514 (0.03061) [-2.92425]	-0.094277 (0.10245) [-0.92020]	-0.127300 (0.02531) [-5.02905]	-1.113585 (0.65315) [-1.70495]
D(LNBL_SA(-1))	0.460456 (0.12306) [3.74157]	-0.804584 (0.41189) [-1.95339]	-0.179319 (0.10177) [-1.76208]	-5.283317 (2.62585) [-2.01204]
D(LNBL_SA(-2))	0.009674 (0.10277) [0.09414]	0.184632 (0.34395) [0.53679]	0.056536 (0.08498) [0.66528]	-0.672008 (2.19275) [-0.30647]
D(LNPP_SA(-1))	-0.020776 (0.03421) [-0.60726]	-0.566453 (0.11451) [-4.94688]	-0.038617 (0.02829) [-1.36499]	0.315210 (0.73000) [0.43180]
D(LNPP_SA(-2))	-0.114470 (0.03347) [-3.41965]	-0.257937 (0.11204) [-2.30227]	0.017683 (0.02768) [0.63882]	0.532014 (0.71424) [0.74486]
D(LNGDP_SA(-1))	-0.311918 (0.18694) [-1.66853]	0.296777 (0.62568) [0.47432]	-0.076876 (0.15459) [-0.49730]	-2.734314 (3.98882) [-0.68550]
D(LNGDP_SA(-2))	0.052786 (0.18470) [0.28579]	0.411437 (0.61817) [0.66557]	-0.118591 (0.15273) [-0.77647]	-2.336752 (3.94091) [-0.59295]
D(R(-1))	-0.025837 (0.00710) [-3.63809]	-0.050600 (0.02377) [-2.12877]	0.015676 (0.00587) [2.66931]	0.668923 (0.15153) [4.41438]
D(R(-2))	0.006716 (0.00833) [0.80581]	-0.089380 (0.02790) [-3.20397]	-0.007800 (0.00689) [-1.13163]	-0.319785 (0.17784) [-1.79811]

R-squared	0.653949	0.436126	0.532278	0.420243
Adj. R-squared	0.600710	0.349376	0.460321	0.331050
Sum sq. resids	0.005127	0.057434	0.003506	2.334250
S.E. equation	0.009930	0.033234	0.008211	0.211871
F-statistic	12.28336	5.027400	7.397158	4.711592
Log likelihood	199.6592	125.9684	211.2515	12.97184
Akaike AIC	-6.251122	-3.835029	-6.631197	-0.130224
Schwarz SC	-5.939682	-3.523589	-6.319756	0.181216
Mean dependent	0.031402	0.015347	0.025489	-0.012295
S.D. dependent	0.015714	0.041202	0.011177	0.259045

Determinant resid covariance (dof adj.)	2.55E-13
Determinant resid covariance	1.35E-13
Log likelihood	557.6224
Akaike information criterion	-16.93844
Schwarz criterion	-15.51966

Table 19 VECM estimation, China

VEC Granger Causality/Block Exogeneity Wald Tests
Date: 05/18/17 Time: 14:17
Sample: 2001Q1 2016Q4
Included observations: 61

Dependent variable: D(LNBL_SA)

Excluded	Chi-sq	df	Prob.
D(LNPP_SA)	11.93999	2	0.0026
D(LNGDP_SA)	3.150501	2	0.2070
D(R)	13.38146	2	0.0012
All	44.13327	6	0.0000

Dependent variable: D(LNPP_SA)

Excluded	Chi-sq	df	Prob.
D(LNBL_SA)	3.976301	2	0.1369
D(LNGDP_SA)	0.570575	2	0.7518
D(R)	16.62535	2	0.0002
All	25.98846	6	0.0002

Dependent variable: D(LNGDP_SA)

Excluded	Chi-sq	df	Prob.
D(LNBL_SA)	3.129844	2	0.2091
D(LNPP_SA)	3.132274	2	0.2089
D(R)	7.804656	2	0.0202
All	18.23635	6	0.0057

Dependent variable: D(R)

Excluded	Chi-sq	df	Prob.
D(LNBL_SA)	5.950042	2	0.0510
D(LNPP_SA)	0.597910	2	0.7416
D(LNGDP_SA)	0.694725	2	0.7065
All	7.104532	6	0.3113

Table 20 Granger causality test, China

Vector Error Correction Estimates

Vector Error Correction Estimates
Date: 07/22/17 Time: 01:15
Sample (adjusted): 2002Q3 2016Q2
Included observations: 56 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1			
Z2(-1)	1.000000			
Z1(-1)	-0.401428 (0.10242) [-3.91960]			
Y3(-1)	-0.184283 (0.13595) [-1.35553]			
Y4(-1)	-0.000482 (0.00180) [-0.26772]			
C	0.000969			
Error Correction:	**D(Z2)**	**D(Z1)**	**D(Y3)**	**D(Y4)**
CointEq1	-1.567244 (0.47944) [-3.26889]	1.028918 (0.45455) [2.26357]	-0.101900 (0.32753) [-0.31111]	-26.00534 (11.1801) [-2.32603]
D(Z2(-1))	-2.56E-06 (0.42820) [-6.0e-06]	-0.615778 (0.40597) [-1.51681]	0.074703 (0.29253) [0.25537]	14.74012 (9.98510) [1.47621]
D(Z2(-2))	0.232192 (0.32133) [0.72259]	-0.138186 (0.30465) [-0.45358]	-0.122536 (0.21952) [-0.55820]	11.14606 (7.49317) [1.48749]
D(Z2(-3))	0.230991 (0.17479) [1.32151]	0.136693 (0.16572) [0.82484]	-0.046178 (0.11941) [-0.38671]	5.872089 (4.07601) [1.44065]
D(Z1(-1))	-0.959394 (0.17866) [-5.36994]	-0.430366 (0.16939) [-2.54074]	-0.042153 (0.12205) [-0.34536]	-8.832965 (4.16618) [-2.12016]
D(Z1(-2))	-0.669506 (0.16684) [-4.01280]	-0.372995 (0.15818) [-2.35801]	-0.056505 (0.11398) [-0.49574]	-6.407903 (3.89060) [-1.64702]
D(Z1(-3))	-0.350255 (0.14141) [-2.47684]	0.084821 (0.13407) [0.63265]	-0.045197 (0.09661) [-0.46785]	-3.278047 (3.29760) [-0.99407]

	(0.26691)	(0.25305)	(0.18234)	(6.22399)
	[-1.03105]	[0.28038]	[-1.56184]	[-0.31320]
D(Y4(-1))	0.015489	0.008229	-0.007935	0.060024
	(0.00726)	(0.00688)	(0.00496)	(0.16929)
	[2.13359]	[1.19559]	[-1.60005]	[0.35458]
D(Y4(-2))	-0.004948	-0.000611	0.005661	-0.238342
	(0.00681)	(0.00646)	(0.00465)	(0.15880)
	[-0.72655]	[-0.09464]	[1.21692]	[-1.50087]
D(Y4(-3))	-0.008790	-0.009624	0.001073	-0.067955
	(0.00644)	(0.00610)	(0.00440)	(0.15013)
	[-1.36541]	[-1.57678]	[0.24396]	[-0.45266]
C	9.83E-05	4.59E-05	-8.07E-05	0.004118
	(0.00126)	(0.00120)	(0.00086)	(0.02949)
	[0.07774]	[0.03830]	[-0.09342]	[0.13961]
R-squared	0.861907	0.602903	0.260858	0.495646
Adj. R-squared	0.819164	0.479992	0.032076	0.339537
Sum sq. resids	0.003690	0.003317	0.001722	2.006419
S.E. equation	0.009373	0.008886	0.006403	0.218568
F-statistic	20.16487	4.905197	1.140205	3.174993
Log likelihood	190.1106	193.0956	211.4482	13.75144
Akaike AIC	-6.289663	-6.396270	-7.051722	0.008877
Schwarz SC	-5.783325	-5.889932	-6.545384	0.515215
Mean dependent	3.99E-05	-0.000107	-3.55E-05	0.000000
S.D. dependent	0.022041	0.012323	0.006508	0.268944

Determinant resid covariance (dof adj.)	7.88E-15
Determinant resid covariance	2.49E-15
Log likelihood	623.6554
Akaike information criterion	-20.13055
Schwarz criterion	-17.96053

Table 21 VECM estimation, U.S.

VEC Granger Causality/Block Exogeneity Wald Tests
Date: 07/22/17 Time: 01:43
Sample: 2001Q1 2016Q2
Included observations: 56

Dependent variable: D(Z2)

Excluded	Chi-sq	df	Prob.
D(Z1)	30.35497	3	0.0000
D(Y3)	3.815305	3	0.2821
D(Y4)	9.595054	3	0.0223
All	43.44234	9	0.0000

Dependent variable: D(Z1)

Excluded	Chi-sq	df	Prob.
D(Z2)	8.573980	3	0.0355
D(Y3)	7.591325	3	0.0553
D(Y4)	5.851817	3	0.1190
All	18.55427	9	0.0293

Dependent variable: D(Y3)

Excluded	Chi-sq	df	Prob.
D(Z2)	3.444338	3	0.3281
D(Z1)	0.317568	3	0.9567
D(Y4)	4.109313	3	0.2499
All	5.268027	9	0.8103

Dependent variable: D(Y4)

Excluded	Chi-sq	df	Prob.
D(Z2)	2.568854	3	0.4630
D(Z1)	4.805480	3	0.1866
D(Y3)	7.260323	3	0.0640
All	11.29110	9	0.2563

Table 22 Granger causality test, U.S.

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