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Bank Credit and Housing Prices in China: Evidence from a TVP-VAR Model with Stochastic Volatility

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Abstract: Housing prices in China have been rising rapidly in recent years, which is a cause for concern for China's housing market. Does bank credit influence housing prices? If so, how? Will the housing prices affect the bank credit system if the market collapses? We aim to study the dynamic relationship between housing prices and bank credit in China from the second quarter of 2005 to the fourth quarter of 2017 by using a time-varying parameter vector autoregression (VAR) model with stochastic volatility. Furthermore, we study the relationships between housing prices and housing loans on the demand side and real estate development loans on the supply side, separately. Finally, we obtain several findings. First, the relationship between housing prices and bank credit shows significant time-varying features; second, the mutual effects of housing prices and bank credit vary between the demand side and supply side; third, influences of housing prices on all kinds of bank credit are stronger than influences in the opposite direction.

Keywords: housing price; bank credit; housing loans; real estate development loans; TVP-VAR model

1. Introduction

The importance of the link between the housing market and macroeconomic activity in China has been proven with plenty of evidence in the literature (e.g., Hong 2014; Cai and Wang 2018). Over the last decade, the real estate market has made a significant contribution to the Chinese macroeconomy. As shown in Figure 1, the real estate industry contributions to GDP and the tertiary industry have been maintained at over 5% and 12%, respectively. Meanwhile, one drastic decline was observed in 2008 due to the global financial crisis. That crisis was directly caused by the decline of the US GDP in the third quarter of 2008, which did not revive until the first quarter of 2010. It was triggered by a sharp decline in housing prices after the collapse of the property bubble, leading to mortgage delinquencies, foreclosures, and the devaluation of housing-related securities.

After the marketization of real estate in China, which began with the reform of the housing system in 1979, housing prices have shown an increasing trend, especially into the 21st century. In particular, from the first quarter of 2005 to the third quarter of 2017, the real housing price increased rapidly from 2923 Yuan/m^2 to 5424 Yuan/m^2. On the other hand, the amount of real medium- and long-term loans in China increased nearly 6.5 times over the same period. Meanwhile, the variation in housing prices and bank credit showed significant consistency. Thus, in order to avoid suffering the same fate as the US, i.e., the collapse of a real estate bubble affecting the whole Chinese economy, the relationship between housing market activity and bank credit is noteworthy.

In fact, many empirical studies have investigated the relationship between housing prices and credit. That bank credit and the housing price have a mutual effect is supported by plenty of evidence in the literature. For instance, Collyns and Senhadji (2002) found that the growth of bank credit has had a certain contemporaneous effect on residential property prices in four East Asian countries: Hong Kong, Korea, Singapore, and Thailand. They concluded that bank lending contributed significantly to the real estate bubble in Asia prior to the 1997 East Asian crisis. The findings of Mora (2008) prove that bank lending is a possible explanation for the Japanese real estate boom during the 1980s. Gimeno and Carrascal (2010) found that credit had a positive causality on the housing price in Spain when the credit aggregate departed from its long-run level. Gerlach and Peng (2005) examined the relationship between property prices and bank lending in Hong Kong, and their results suggest that the development of property prices influences bank lending.[1]

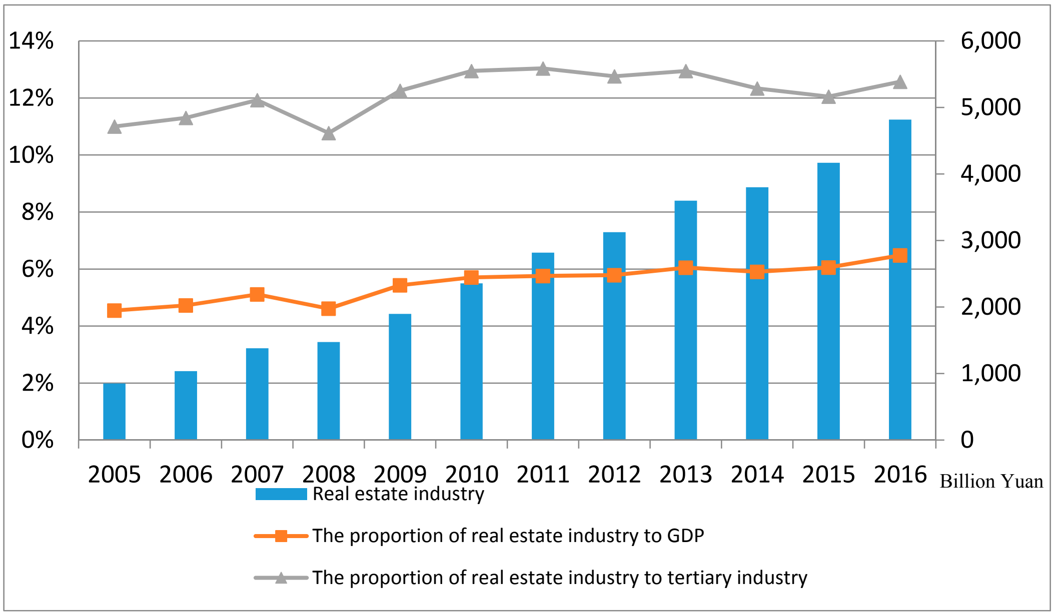

Figure 1. The Chinese real estate industry contributions to the tertiary industry and GDP in billions of Yuan. Source: China Statistics Bureau.

Davis and Zhu (2011) argued that the effect of commercial property prices on credit is stronger than the reverse. More importantly, their research showed that because bank credit affects both the property buyer and the developer, when bank credit is extended, it may boost demand and stimulate an increase in housing prices. Credit has a positive effect on commercial property prices in the short run. Meanwhile, the extension of bank credit may also finance new construction, and housing prices will finally adjust downwards through an improvement in supply. However, because of the lags in supply, the negative effect will only be felt in the long term.

Based on this perspective, this study makes two contributions. First, we not only observe the relationship between the housing price and bank credit in market as a whole but also divide the market into two parts: the demand side and the supply side. We intend to quantify the different relationships between housing prices and bank credit on these two fronts. Hence, this paper compares three different variable sets from the market as a whole, and from the demand and supply sides of the housing market.

The second contribution is that unlike most previous studies which were based on the simple vector autoregression (VAR) model, we adopt the time-varying parameter VAR (TVP-VAR) model with stochastic volatility which delivers more accurate empirical results. The simple VAR model has an obvious limitation: linear coefficients are time-invariant. However, in reality, the economic structure and the relationships among economic variables are more complicated and change over time, which means that the linear and time-invariant features of a simple VAR model are unrealistic.

[1] Yuan and Hamori (2014) analyzed the crowding out effect of affordable and unaffordable housing in China.

However, the TVP-VAR model can circumvent this problem perfectly. As stated by Nakajima (2011), "The TVP-VAR model enables us to capture the possible time-varying nature of the underlying structure in the economy in a flexible and robust manner". Moreover, stochastic volatility, which also influences the data generating process of economic variables and was originally proposed by Black (1976), may cause misspecification if it is ignored during analysis. Nakajima (2011) estimated the TVP regression model with stochastic volatility and constant volatility for a given set of simulated data, finding that the estimation result of the model with stochastic volatility was closer to the true value. Tian and Hamori (2016) use a time-varying structural vector auto-regression model with stochastic volatility to study the financial shock transmission mechanism. For this reason, we also incorporate stochastic volatility into the TVP-VAR model. On the other hand, due to the intractability of the likelihood function, stochastic volatility makes the estimation difficult. To circumvent this problem, we also use Markov chain Monte Carlo (MCMC) methods in the context of a Bayesian inference to estimate the model.

In this paper, our empirical results are presented in three parts. First, we find that the relationship between housing prices and bank credit has significant time-varying features. Second, the mutual effect between housing prices and bank credit varies on both the demand side and the supply side. Third, the influences of housing prices on all kinds of bank credit are stronger than influences in the opposite direction.

The remainder of the article is organized as follows. Section 2 presents a theoretical analysis of the interaction effect between bank credit and housing prices based on references. Section 3 introduces the model specifications. Section 4 discusses the data and the identification procedure. Section 5 shows the empirical results of each set of variables, and Section 6 presents the conclusions.

2. Theoretical Analysis of the Interaction Effect between Bank Credit and Housing Prices

Bank credit is considered to influence the housing market. Although bank credit is considered to have a positive effect on housing prices in general, in fact, the effect should not be understood as a whole, as it not only depends on the objects of bank credit—both the supply side of housing and the demand side—but it also depends on time. The effect of bank credit on housing prices may differ because of differences in influences on the two sides of the housing market. In addition, the different periods and lengths of time will also change the effect.

On the demand side, there is no doubt that housing loans are the main way for general consumers to buy houses. As housing loans expand, the demand for housing will also increase. This demand is not only for personal use but also for investment. In China, property is considered to be a good investment due to its ability to increase in value. Once housing loans can be obtained easily, speculative demand for property can also be stimulated with the help of bank funds, especially in the short term, because the supply of housing is inelastic, so prices will increase as a result of influences from the demand side.

On the supply side, the long-term and the short-term effects of real estate development loan[2] on housing prices are different. In China, real estate development loans are the main source of capital for constructors. According to calculations by Qin and Yao (2012), from 1998 to 2010, the average annual proportion of capital gained directly by banks from real estate development investment was more than 20.78%, while if the capital gained indirectly by banks, such as from down payments and personal mortgages, is also counted[3], this proportion is more than 66.81%. Thus, it is not difficult to see how important bank credit is to the constructors. In fact, since the marketization of real estate in China, the housing market in China has always been a seller's market in which the constructors have more bargaining power than the buyers. Meanwhile, in the short term, bank credit can relieve the financial

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[2] In this paper, real estate development loan refers to the loan that bank issues to the borrower to finance construction of real estates and supportive facilities.

[3] In China, the presale of commercial residential houses allows developers to use the capital that consumers borrow from the bank for construction.

pressure of constructors, further enhancing their bargaining power and pushing up housing prices. However, in the long term, high real estate development also leads to a high supply of housing, and after the 2008 financial crisis, a high investment in the housing market led to a "high inventory" problem in China. In October 2016, the number of residential houses for sale hit another historical high. Many cities in China that have a high inventory of housing face huge pressure to reduce their numbers of unsold homes. Thus, high real estate loans will also make housing prices decrease in the long term because of oversupply in the long term, as concluded by Davis and Zhu (2011).

On the other hand, the growth of housing prices also has a strong effect on bank credit. In periods when housing prices continue to rise, banks are likely to underestimate the risk of credit on real estate development, causing them to expand their credit supply to the real estate industry.

For general consumers, based on research by Goodhart and Hofmann (2008) and other references, the growth of housing prices will mainly affect housing loans in three ways: the wealth effect, the collateral effect, and the expectation effect. First, the growth of housing prices via the wealth effect makes individuals willing to get more credit from the bank. Under the life cycle model of household consumption, a permanent increase in housing wealth can increase both household spending and borrowing if individuals want to smooth consumption over their life cycles. Second, since property is a general collateral item, a growth in housing prices can also increase the collateral value of individuals which can lead to lenders getting credit from the bank more easily. Third, the expectation effect explains that if housing prices begin to rise, consumers will anticipate that they will keep increasing, which encourages them to get a bigger housing loan to purchase property as soon as possible.

For the constructors, rises in housing prices can increase their expected investment return in real estate development, which will inevitably encourage them to expand their investment scale and attract new companies to enter the field. Since bank credit is the most important source of capital for the constructors, credit demand will significantly increase.

3. Time-Varying Parameter VAR Model with Stochastic Volatility

This paper follows Nakajima (2011) for the time-varying TVP-VAR model with stochastic volatility[4]. Consider the time varying structural VAR model

$$A_t y_t = B_{0t} + B_{1t} y_{t-1} + \cdots + B_{st} y_{t-s} + u_t, \quad t = s+1, \ldots n, \tag{1}$$

where y_t is a $k \times 1$ vector of observed variables, B_{0t} is an $k \times 1$ vector of the intercept term, $A_t, c_t, B_{1t}, \ldots, B_{st}$ are $k \times k$ matrices of time varying coefficients. The disturbance u_t is a $k \times 1$ time-varying structural shock, and it is assumed that $u_t \sim N(0, \sum_t \sum_t)$, where

$$\sum_t = \begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{k,t} \end{pmatrix}$$

The simultaneous relations of the structural shock are specified by recursive identification, assuming that A_t is lower-triangular. Meanwhile, it is important to note that A_t is allowed to vary over time, which implies that an innovation to the i-th variable has a time invariant effect on the j-th variable:

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4 Hereafter, for simplicity, we use the "TVP-VAR model" to indicate the model with stochastic volatility.

$$A_t = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1,t} & \cdots & a_{kk-1,t} & 1 \end{pmatrix}$$

Thus, Equation (1) can be rewritten as the following reduced form VAR model:

$$y_t = C_{0t} + C_{1t}y_{t-1} + \cdots + C_{st}y_{t-s} + A_t^{-1}\sum_t \varepsilon_t, \quad \varepsilon_t \sim N(0, I_k), \tag{2}$$

where $C_{it} = A_t^{-1}B_{it}$, for $i = 0, \ldots, s$. By stacking the elements in the rows of C_i's to a vector ς_t ($k^2(s+1) \times 1$ vector), the model can be written as follows:

$$y_t = X_t\varsigma_t + A_t^{-1}\sum_t \varepsilon_t. \tag{3}$$

$$X_t = I_k \otimes \left(1, y'_{t-1}, \cdots, y'_{t-s}\right),\ t = s+1, \cdots, n$$

where $\otimes$ denotes the Kronecker product. Meanwhile, following Primiceri (2005), $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, \cdots, a_{k,k-1})'$ is a stacked vector of the lower-triangular elements, assuming ς_t, A_t, and $\sum_t$ all change over time.

If the variance is assumed to be constant while the coefficients are time-varying, it will cause the estimate parameters to be biased, because the possibility of volatility variation is ignored (Nakajima, 2011). To avoid this misspecification, stochastic volatility is also incorporated into the TVP-VAR model. It is assumed that the log-volatility is $h_t = (h_{1t}, \cdots, h_{kt})'$, $h_{jt} = \log \sigma_{jt}^2$, and for $j = 1, \cdots, k$, $t = s+1, \ldots, n$, it is also modeled to follow a random walk. The variances (σ_{jt}^2) are assumed to evolve as geometric random walks belonging to the class of models known as stochastic volatility.[5]

The dynamics of the model's time varying parameters in (3) and the stochastic volatility are specified as follows:

$$\begin{aligned} \varsigma_{t+1} &= \varsigma_t + u_{\varsigma t}, \\ a_{t+1} &= a_t + u_{at}, \\ h_{t+1} &= h_t + u_{ht}, \end{aligned} \quad \begin{pmatrix} \varepsilon_t \\ u_{\varsigma t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & O & O & O \\ O & \sum_\varsigma & O & O \\ O & O & \sum_a & O \\ O & O & O & \sum_h \end{pmatrix}\right), \tag{4}$$

for $t = s+1, \cdots, n$, where $\varsigma_{s+1} \sim N(\mu_{\varsigma_0}, \sum_{\varsigma_0})$, $a_{s+1} \sim N(\mu_{a_0}, \sum_{a_0})$ and $h_{s+1} \sim N(\mu_{h_0}, \sum_{h_0})$.

Moreover, in this paper, we also make two assumptions that follow Nakajima (2011) and need to be stated. First, the assumption of a lower-triangular matrix for A_t is the recursive identification for the VAR system. Second, for simplicity, we assume that $\sum_a$ and $\sum_h$ are diagonal matrices.

4. Data and Settings

Table 1 shows all variables in our model. In out paper we use a four-variable TVP-VAR model to estimate the quarterly seasonally-adjusted data from the second quarter of 2005 to the fourth quarter of 2017 in China[6]. Furthermore, we estimated three different sets of variables. The first set was defined as $y_t = (IR_t, GDP_t, BC_t, HP_t)$, the second is $y_t = (IR_t, GDP_t, HL_t, HP_t)$, and the third is

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5 Here, we use the log-normal SV model, which was originally proposed by Taylor (1986). The simplest model can also be defined: $y_t = \gamma \exp\left(\frac{h_t}{2}\right)$, $h_{t+1} = \phi h_t + \eta_t$, $\eta_t \sim NID\left(0, \sigma_\eta^2\right)$, $t = 0, \ldots, n-1$, $\gamma > 0$. For more details on the statistical aspects of ARCH and stochastic volatility, see Shephard (1996). Yang and Hamori (2018) compared the performances of the GARCH and SV models to analyze international agricultural commodity prices.

6 Because of the availability of data, we started the sample period in the second quarter of 2005.

$y_t = (IR_t, GDP_t, DL_t, HP_t)$, where IR refers to the logarithmic growth of the Inter Bank Offered Rate (IBOR) as the interest rate variable; GDP refers to the logarithmic growth of the real GDP; BC refers to the logarithmic growth of the real medium and long term loans as the bank credit variable and reflects credit in the whole market; HP refers to the logarithmic growth of the real price of housing; HL refers to the logarithmic growth of housing loans and reflects credit on the demand side; and DL refers to the logarithmic growth of real estate development loans and reflects credit on the supply side.

Table 1. Model Variables.

Variable	Data	Data Source
Housing Prices (HP)	The logarithmic growth of real price of housing	CEIC database
Interest Rate (IR)	The logarithmic growth of the Inter Bank Offered Rate (IBOR)	CEIC database
GDP	The logarithmic growth of real GDP	CEIC database
Bank Credit (BC)	The logarithmic growth of real medium- and long-term loan	CEIC database
Housing Loan (HL)	The logarithmic growth of housing loan	CEIC database
Real Estate Development Loan (DL)	The logarithmic growth of real estate development loan	CEIC database

The variables were all sourced from the China Entrepreneur Investment Club (CEIC) database[7].

In the first set of variables, we intended to study the relationship between bank credit and housing prices. The reason we chose the medium and long term loans as the variables of bank credit was because they influence both property buyers and developers.

In the second and third sets of variables, we wanted to study the relationship between bank credit and the housing price on the supply side and the demand side separately. For this reason, we chose housing loans for the demand side and real estate development loans for the supply side.

In addition, the cycle of bank credit can be significantly influenced by the interest rate. McQuinn and O'Reilly (2008) also showed the importance of interest rates not only in determining the housing price, but also in reflecting the availability of credit. Hence, we added the interest rate into the model as well. As the lending or mortgage rates in China are strictly regulated, IBOR is a better indicator of demand and supply in all financial markets. For this reason, the interest rate data used in this paper refers to the Inter Bank Offered Rate. Meanwhile, in consideration of the influence of macroeconomics, GDP was also added into our model.

The housing price represents the average price of commercial property in China.

Table 2 presents the descriptive statistics for the logarithmic growth of variables in the model. The Jarque–Bera statistics, which are used to detect whether the logarithmic growth of variables is normally distributed, rejected normality at a 5% significance level in all variables. Figure 2 plots the logarithmic growth of bank credit and housing prices.

Meanwhile, before the estimation, it was necessary to perform unit root tests to ensure the stationarity of data. As presented in Table 3, all variables in the model were tested for stationarity using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Dickey Fuller GLS (DF-GLS) tests. The ADF test was proposed in 1981 and has become the most popular of the many competing tests. The PP test is an alternative unit root testing approach of the ADF test which was proposed in 1988. The DF-GLS test was proposed in 1992 and is considered an improved version of the ADF test. Many studies use many different methods simultaneously to test for stationarity (e.g., Mwabutwa et al. 2016), to make their results more convincing. All of the tests shown in Table 3 demonstrate that the variables were stationary at all levels. Subsequently, we were able to build a stable constant parameter VAR model to obtain the lags of the TVP-VAR, which were based on application of the Schwarz criterion to the stable constant parameter VAR for all sets of variables.

[7] The CEIC database belongs to CEIC Data Company Ltd., whose headquarters are in Hong Kong. This company compiles and updates economic and financial data series such as banking statistics, construction, and properties for economic research on emerging and developed markets, especially in China.

Table 2. Descriptive statistics.

	HP	IR	GDP	BC	HL	DL
Sample Size	51	51	51	51	51	51
Mean	0.5890	−0.6814	1.0724	1.5791	1.9800	1.7245
Std. Dev.	1.2609	8.4497	0.9204	0.9286	0.9912	1.4552
Skewness	−0.3381	−0.0905	−0.5015	1.6381	0.9906	2.1208
Kurtosis	4.7143	5.0809	5.4204	6.0717	3.7497	13.9351
Maximum	3.6529	23.7312	2.7776	4.5034	4.8360	8.9988
Minimum	−3.7025	−26.2599	−1.6036	−0.0115	0.3222	−1.9866
Jarque–Bera	7.2166	9.2712	14.5874	42.8576	9.5353	292.3303
Probability	0.0271	0.0097	0.0006	0.0000	0.0085	0.0000

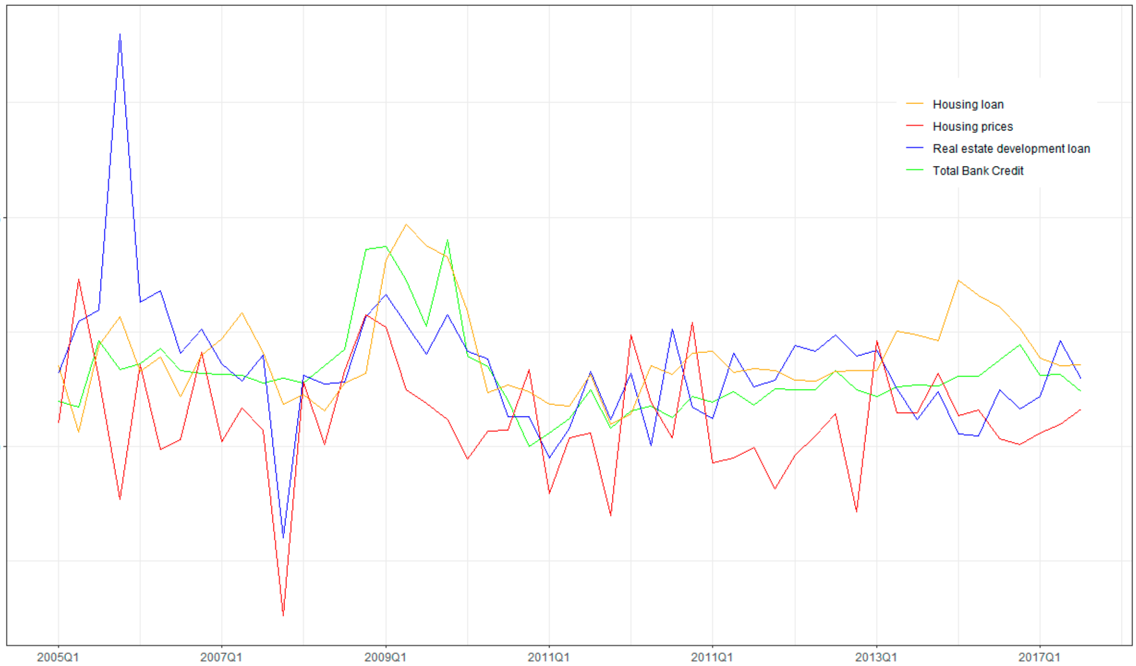

Figure 2. The logarithmic growth of bank credit and housing prices.

Table 3. Testing for stationarity.

Variables	ADF	PP	DF-GLS
	Level	Level	Level
HP	−4.3138 ***	−7.3650 ***	−7.3510 ***
IR	−3.4648 **	−3.1574 **	−3.4111 ***
GDP	−6.5760 ***	−6.5925 ***	−5.0991 ***
BC	−2.8507 *	−2.9110 *	−2.7068 ***
HL	−8.7130 ***	−8.5561 ***	−7.2918 ***
DL	−4.7565 ***	−4.8917 ***	−4.7964 ***

Notes: To employ the unit root test, we used the intercepts of all variables; the symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. ADF: Augmented Dickey–Fuller; PP: Phillips–Perron; DF-GLS: Dickey Fuller GLS.

Finally, before starting the MCMC simulation, the following priors were assumed for the i-th diagonals of the covariance matrices, which is in accordance with Nakajima (2011):

$$\left(\sum_{\varsigma}\right)_i^{-2} \sim Gamma(40, 0.02), \left(\sum_{\alpha}\right)_i^{-2} \sim Gamma(40, 0.02), \left(\sum_{h}\right)_i^{-2} \sim Gamma(40, 0.02).$$

For the initial state of the time-varying parameter, rather flat priors are set; $\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0} = 0$, and $\sum_{\beta_0} = \sum_{a_0} = \sum_{h_0} = 10 \times I$.

5. Empirical Results

This paper estimated the TVP-VAR model using a simulation by drawing M = 20,000 samples with the Markov Chain Monte Carlo (MCMC) algorithm and discarding the initial 2000 samples in the burn-in period.

5.1. Bank Credit and Housing Prices

Table 4 shows the estimated results of selected parameters in the TVP-VAR model for the first set of variables: (IR, GDP, BC, HP). The table shows the posterior mean, posterior standard deviation, 95 percent interval, and the Geweke (1992) convergence diagnostics (CD) of the *i*-th diagonal elements of $(\sum_{\varsigma})_i$, $(\sum_a)_i$ and $(\sum_h)_i$, as well as the inefficient factors computed by using MCMC sampling. In the estimated results, all Geweke values were less than the 5% significance level based on the convergence diagnostics of 1.96 in the first set of variables, indicating acceptance of the null hypothesis of convergence to the posterior distribution. Meanwhile, the inefficient factors were rather low, which implies that the number of efficient samples used for the parameters and stated variables were sufficient, the minimum being approximately M/100 = 200.

Figure 3 illustrates the sample auto-correlation, sample paths, and the posterior densities of the parameters for the first set of variables. The sample auto-correlations in the first row of each figure all decreased quickly and ranged slightly around the 0 level, suggesting that most samples had low auto-correlation. Also, the sample paths in the second row in each figure were all very stable, indicating that the samples produced from the MCMC method were efficient.

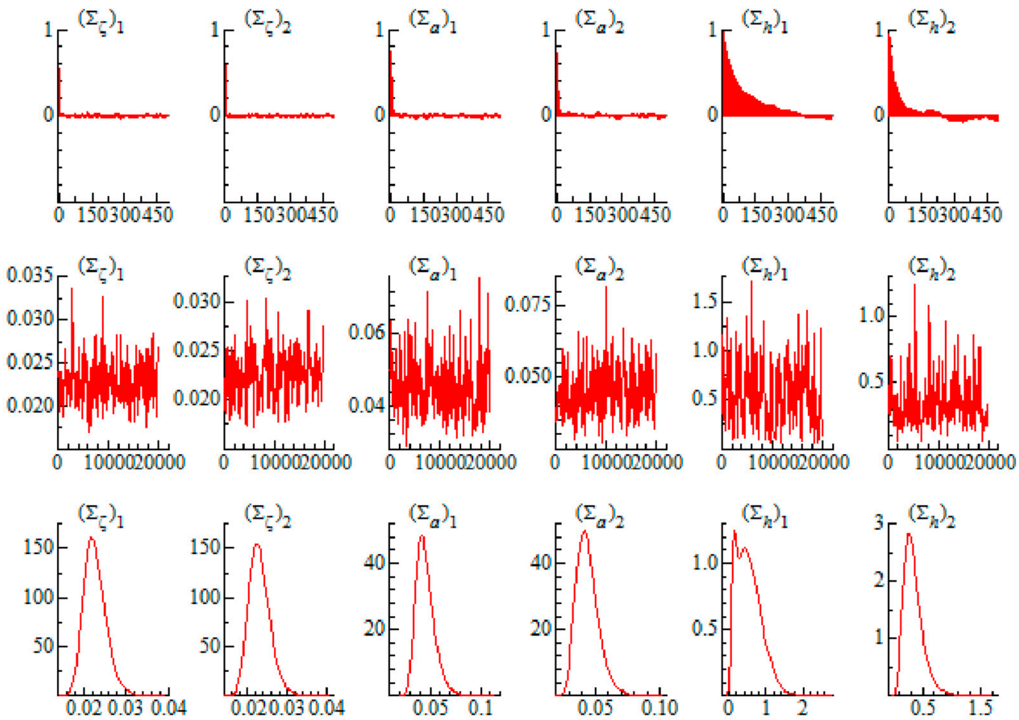

Figure 3. Estimation results of parameters in the TVP-VAR model (bank credit–housing prices). Notes: The figure shows sample auto-correlations (**top**), sample paths (**middle**), and posterior densities (**bottom**). In the top figures, the *x*-axis is the sample auto-correlation, and the *y*-axis is the lag; in the middle figures, the *x*-axis is the sampled value, and the *y*-axis is the iteration; in the bottom figure, the *x*-axis is the probability density, and the *y*-axis is the sampled value. The estimates of Σ_ζ and Σ_a are multiplied by 100.

The Impulse Response Function is considered a useful tool to show the dynamic movements simulated by running the VAR model. For this reason, we performed an impulse response analysis based on the TVP-VAR model. Moreover, for comparison, the results of the standard VAR model, whose parameters are all-invariant, are also shown in Figure 4.

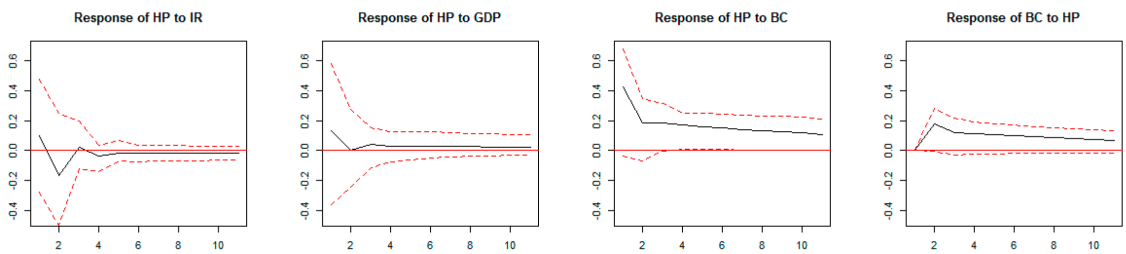

Figure 4. Impulse response based on the standard TVP model for IR, GDP BC, and HP. Notes: This shows the impulse response based on the standard VAR model for the variable set (IR, GDP, BC, HP); the solid line refers to the posterior mean, and the dotted line refers to 95% credible intervals.

In Figure 4, although the impulse responses of housing prices to interest rates were negative in only a few quarters, they were statistically insignificant with 95% confidence intervals throughout the measurement period. The impulse responses of housing prices to GDP were only slightly positive but were also statistically insignificant. Meanwhile, the impulse responses of housing prices to bank credit were positive throughout the measurement period, and they were only statistically insignificant within the first three quarters. In contrast, the impulse responses of bank credit to housing prices also stayed positive for the whole time period and were statistically significant. The standard VAR model showed a positive mutual effect between housing prices and bank credit, but it also cast doubt on the effects of interest rate and GDP on housing prices.

On the other hand, Figure 5 shows the time-varying impulse responses based on the TVP-VAR model, they are drawn in a time-series manner by showing the size of impulses for each quarter, half a year, and year. As shown in Figure 5, remarkably, all of the impulse responses have varied significantly over time. The impulse response of housing price to interest rate in each quarter remained positive until 2009, and was negative thereafter. Meanwhile, the responses for half-year and yearly changes were inverse and remained at a low level. This implies that the housing price can also be controlled by the interest rate, as shown by David (2013), but only in the short term. The quarterly and yearly impulse responses of housing prices to GDP were negative throughout the measurement period and the half-year responses only turned positive a few times.

Table 4. Estimation of selected parameters in the time-varying parameter TVP-VAR model (bank credit–housing prices).

	Mean	St. Dev	95%L	95%U	Geweke	Inef.
$(\Sigma_\varsigma)_1$	0.0227	0.0026	0.0183	0.0286	0.2150	3.9600
$(\Sigma_\varsigma)_2$	0.0230	0.0027	0.0185	0.0290	0.3410	2.8200
$(\Sigma_a)_1$	0.0453	0.0092	0.0310	0.0667	0.0230	8.3900
$(\Sigma_a)_2$	0.0444	0.0086	0.0309	0.0641	0.0930	11.4500
$(\Sigma_h)_1$	0.5335	0.3378	0.0752	1.2870	0.1080	125.3200
$(\Sigma_h)_2$	0.3431	0.1722	0.1036	0.7669	0.6420	63.5400

Notes: This is the estimation result of selected parameters in the TVP-VAR model for the variable set (IR, GDP, BC, HP). It shows that the means, standard deviations, the 95% credible intervals (upper and lower), the Geweke (1992) convergence diagnostics, and the number of inefficient samples are part of the diagonal elements of the covariance matrices; the estimates of Σ_ς and Σ_a are multiplied by 100.

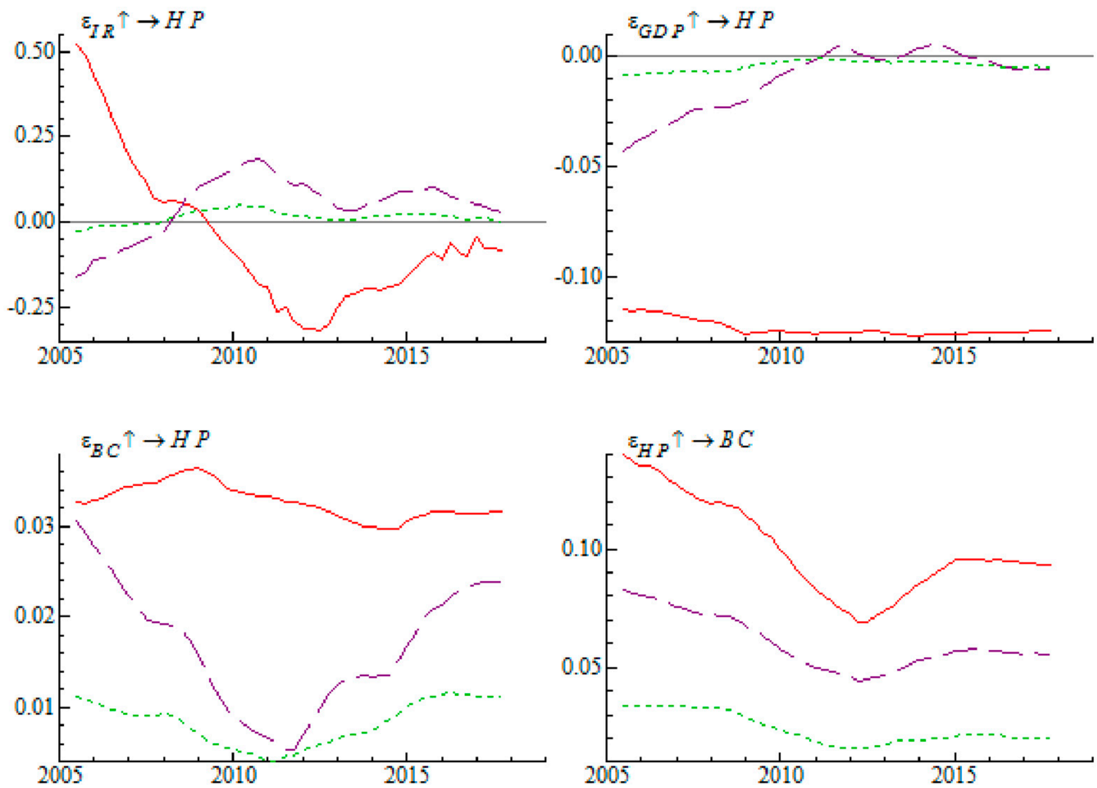

Figure 5. Impulse response for three different horizons. Notes: This shows the impulse response of the TVP-VAR model for the variable set of (IR, GDP, BC, HP); HP represents housing prices, BC represents bank credit, and IR represents the interest rate; the solid line refers to the time-varying impulse responses for each quarter; the dashed line refers to half-year responses; and the dotted line refers to yearly responses.

We can see that both the impulse responses of the housing price to bank credit and the reverse were positive throughout the sample period, which proves that although the mutual effect between housing price and bank credit may vary between the different sides, in the market as a whole, the mutual effect was still positive throughout the sample period in China.

In addition, we can also notice that the effect of the housing price on bank credit was stronger than the influence of bank credit on the housing price. This also implies that the banking and credit system will be greatly affected if the housing price begins to fluctuate wildly.

5.2. Housing Loans and Housing Prices

Table 5 shows the estimated results of the selected parameters in the TVP-VAR model for the second set of variables: (IR, GDP, HL, HP). In the estimated results, all Geweke values were less than the 5% significance level based on the convergence diagnostics of 1.96 in the first set of variables, indicating acceptance of the null hypothesis of convergence to the posterior distribution. Meanwhile, the number of inefficient factors was rather low, which implies that the number of efficient samples for the parameters and stated variables was sufficient, the minimum being approximately M/100 = 200.

Figure 6 illustrates the sample auto-correlation, sample paths, and posterior densities of the parameters for the second set of variables. The sample auto-correlation shown in the first row of each figure decreased quickly and ranged around the 0 level, suggesting that most samples had low auto-correlation. Also, the sample paths shown in the second row of each figure were all very stable, indicating that the samples produced from the MCMC method were efficient.

Figure 7 shows the impulse response functions based on the standard VAR model for the second variable set (IR, GDP, HL, HP). In Figure 7, the impulse responses of housing prices to the interest rate and the impulse responses of housing prices to the GDP are similar to those presented in Section 5.1. Meanwhile, the impulse responses of housing prices to housing loans were positive throughout the sample period but were statistically insignificant at the 95% confidence interval for the first four quarters. In the opposite direction, the impulse responses of housing loans to housing prices were positive and statistically significant throughout the measurement period.

Table 5. Estimation of selected parameters in the TVP-VAR model (housing loans–housing prices).

	Mean	St. Dev	95%L	95%U	Geweke	Inef.
$(\Sigma_\varsigma)_1$	0.0228	0.0027	0.0184	0.0287	0.3550	4.5000
$(\Sigma_\varsigma)_2$	0.0230	0.0027	0.0185	0.0289	0.5260	3.2000
$(\Sigma_a)_1$	0.0445	0.0088	0.0308	0.0650	0.5580	10.3100
$(\Sigma_a)_2$	0.0505	0.0108	0.0336	0.0754	0.4100	12.0700
$(\Sigma_h)_1$	0.4923	0.3177	0.0858	1.1984	0.2590	103.9000
$(\Sigma_h)_2$	0.4434	0.2130	0.1547	0.9810	0.2930	78.8900

Notes: (i) These are the estimation results of selected parameters in the TVP-VAR model for the variable set (IR, GDP, HL, HP). The means, standard deviations, the 95% credible intervals (upper and lower), the Geweke (1992) convergence diagnostics, and the number of inefficient samples are shown; (ii) $(\Sigma_\varsigma)_i$, $(\Sigma_\alpha)_j$, $(\Sigma_h)_k$ are part of the diagonal elements of the covariance matrices; (iii) the estimates of Σ_ς and Σ_a are multiplied by 100.

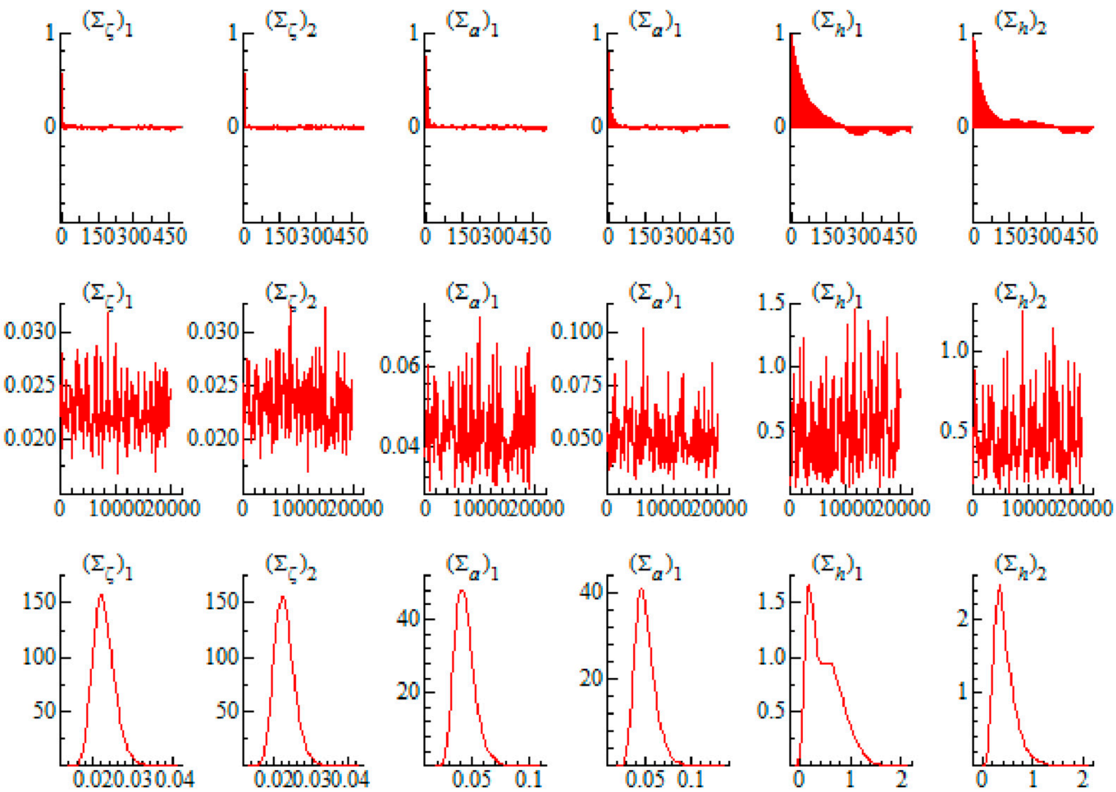

Figure 6. Estimation results of parameters in the TVP-VAR model (housing loans–housing prices). Notes: The figure shows sample auto-correlations (**top**), sample paths (**middle**), and posterior densities (**bottom**); in the top figures, the x-axis is the sample auto-correlation, and the y-axis is the lag; in the middle figures, the x-axis is the sampled value, and the y-axis is the iteration; in the bottom figure, the x-axis is the probability density, and the y-axis is the sampled value; the estimates of Σ_ζ and Σ_a are multiplied by 100.

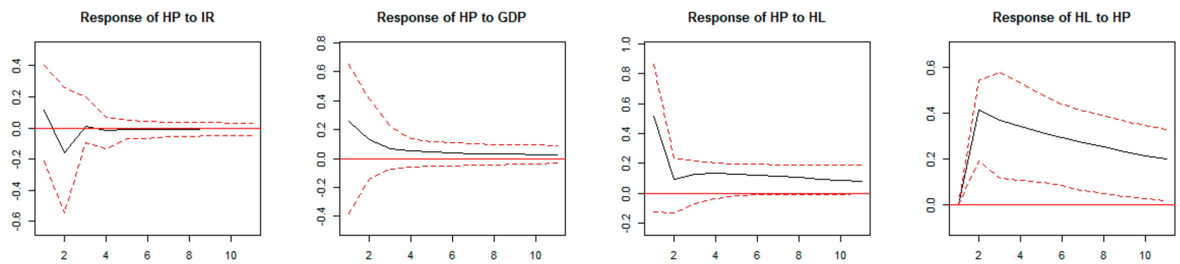

Figure 7. Impulse response based on the standard TVP model for (IR, GDP HL, HP). Notes: This shows the impulse response based on the standard VAR model for the variable set (IR, GDP, BC, HP); the solid line refers to posterior mean, and the dotted line refers to 95% credible intervals.

For comparison, the results of time-varying impulse responses based on TVP-VAR model are shown in Figure 8. They also show the significant time-varying features in each impulse response. Figure 8 shows that the impulse responses of the housing prices and housing loans to the interest rate had a similar variation to that shown in Figure 5. Meanwhile, the impulse response of housing prices to housing loans was positive for the half-year and yearly measurements, and for quarterly measurements in most periods; however, it turned negative after 2013 which implies that in that period, housing prices could not be controlled by housing loans in the short term. In contrast, housing prices also showed a positive effect on housing loans throughout the sample period which coincides with the theory that a growth in housing prices will affect the housing loans via the wealth effect, the collateral effect, and the expectation effect.

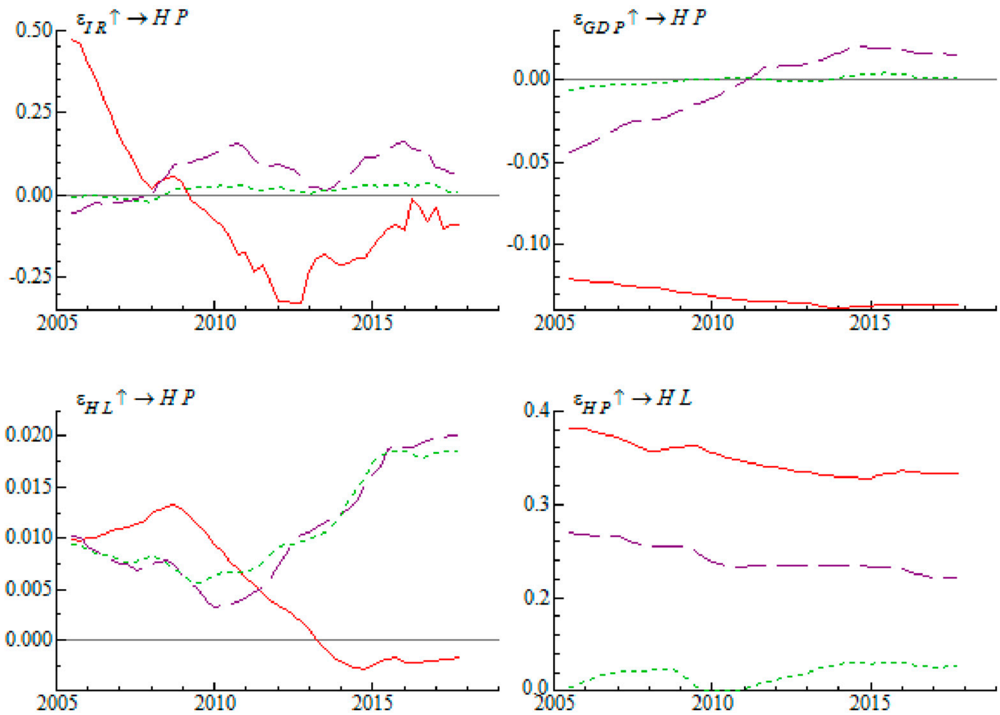

Figure 8. Impulse response for three different horizons. Notes: This shows the impulse response of the TVP-VAR model for the variable set of (IR, GDP, HL, HP); HP represents the housing price, HL represents housing loans, and IR represents the interest rate; the solid line refers to time-varying impulse responses for each quarter; the dashed line refers to half-year responses; and the dotted line refers to yearly responses.

In addition, the effect of housing prices on housing loans was stronger than the influence of housing loans on housing prices.

5.3. Real Estate Development Loan and Housing Prices

Table 6 shows the estimated results of selected parameters in the TVP-VAR model for the third set of variables: (IR, GDP, DL, HP). In the estimated results, all Geweke values were less than the 5% significance level based on the convergence diagnostics of 1.96 in the first set of variables, indicating acceptance of the null hypothesis of convergence to the posterior distribution. Meanwhile, the number of inefficient factors was rather low, which implies that the number of efficient samples for the parameters and stated variables was sufficient, the minimum being approximately M/100 = 200.

Table 6. Estimation of selected parameters in the TVP-VAR model (real estate development loans–housing prices).

	Mean	St. Dev	95%L	95%U	Geweke	Inef.
$(\Sigma_\varsigma)_1$	0.0228	0.0026	0.0183	0.0284	0.4130	2.9400
$(\Sigma_\varsigma)_2$	0.0230	0.0027	0.0184	0.0291	0.3460	4.6700
$(\Sigma_a)_1$	0.0462	0.0096	0.0316	0.0686	0.1720	19.6300
$(\Sigma_a)_2$	0.0599	0.0157	0.0373	0.0971	0.2420	14.9100
$(\Sigma_h)_1$	0.4279	0.2924	0.0743	1.1305	0.5250	138.0900
$(\Sigma_h)_2$	0.4495	0.2496	0.1159	1.1173	0.9050	107.8300

Notes: This table shows the estimation results of selected parameters in the TVP-VAR model for the variable set (IR, GDP, DL, HP). Tt shows means, standard deviations, the 95% credible intervals (upper and lower), the Geweke (1992) convergence diagnostics, and the number of inefficient samples; $(\Sigma_\varsigma)_i$, $(\Sigma_\alpha)_j$, $(\Sigma_h)_k$ are part of the diagonal elements of the covariance matrices; the estimates of Σ_ζ and Σ_a are multiplied by 100.

Figure 9 illustrates sample auto-correlations, sample paths, and the posterior densities of the parameters for the third set of variables. The sample auto-correlations shown in the first row in each figure all decreased quickly and ranged around the 0 level, suggesting that most samples had low auto-correlation. Also, the sample paths shown in the second row in each figure were all very stable, indicating that the samples produced from the MCMC method were efficient.

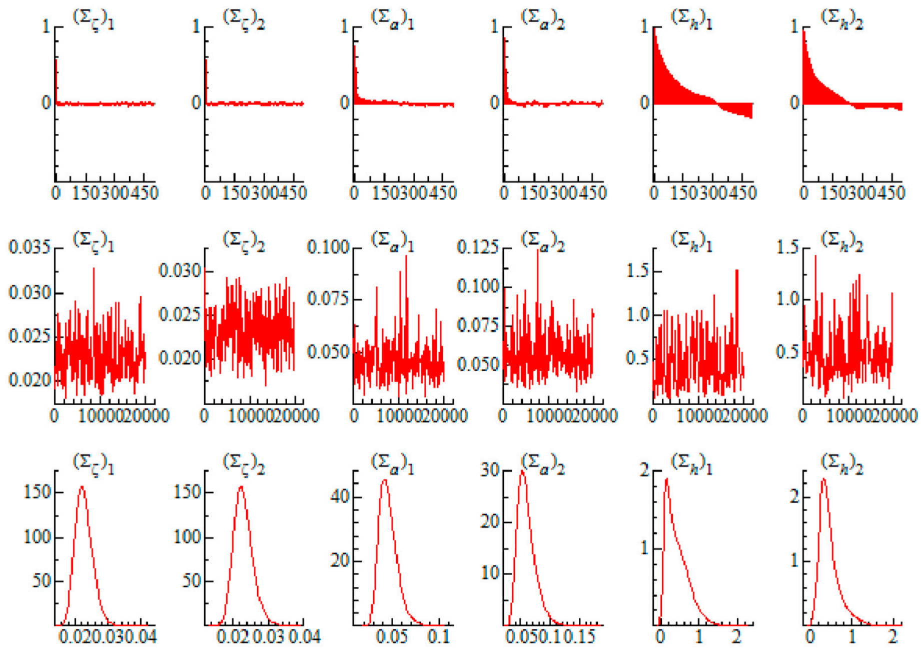

Figure 9. Estimation results of parameters in the TVP-VAR model (real estate development loans–housing prices). Notes: The figure shows sample auto-correlations (**top**), sample paths (**middle**), and posterior densities (**bottom**); in the top figures, the *x*-axis is the sample auto-correlation, and the *y*-axis is the lag; in the middle figures, the *x*-axis is the sampled value, and the *y*-axis is the iteration; in the bottom figures, the *x*-axis is the probability density, and the *y*-axis is the sampled value; the estimates of Σ_ς and Σ_a are multiplied by 100.

Figure 10 shows the impulse response functions based on the standard VAR model for the third variable set (IR, GDP, DL, HP). In Figure 10, it can be seen that the impulse responses of housing prices to real estate development loan were positive but statistically insignificant at the 95% confidence interval within the first three quarters. Meanwhile, it is also interesting to note that the impulse responses of real estate development loans to housing prices were slightly positive but statistically insignificant over all periods.

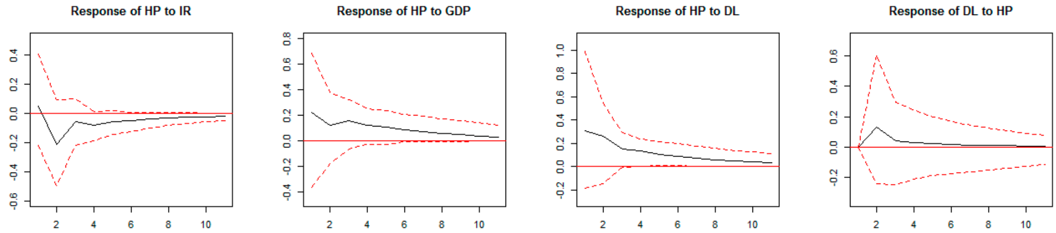

Figure 10. Impulse response based on the standard TVP model for (IR, GDP DL, HP). Notes: This shows the impulse response based on the standard VAR model for the variable set (IR, GDP, DL, HP); the solid line refers to the posterior mean; and the dotted line refers to the 95% credible intervals.

Figure 11 shows the time-varying responses for the third set of variables (IR, GDP, DL, HP), in which we can also see the significant time-varying features in each impulse response. The time-varying impulse response function showed negative responses of real estate development loans to the housing prices over all periods. Although this seems to not coincide with the theoretical analysis in Section 2, there is a possibility that if housing prices continue to rise, real development loans will not expand and may even reduce under government regulation. The impulse responses of the housing price to real estate development loans were also negative over the short-term, half-year and yearly periods. Meanwhile, in the short term, positive responses were seen for one quarter before the middle of 2017. This supports the economic theory that the effects of real estate development loan vary in different periods.

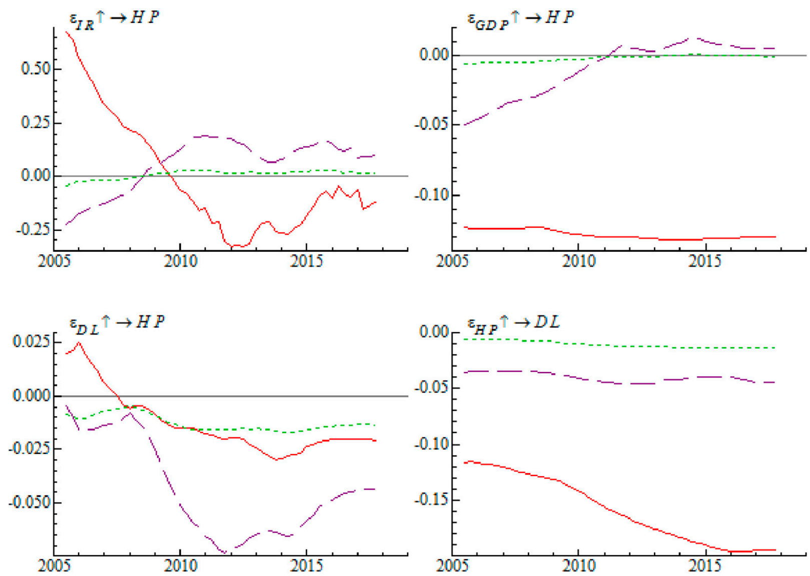

Figure 11. Impulse response for three different horizons. Notes: This shows the impulse response of the TVP-VAR model for the variable set of (IR, GDP, DL, HP); HP represents the housing price, DL represents real estate development loans, and IR represents the interest rate; the solid line refers to time-varying impulse responses for each quarter, the dashed line refers to half-year responses, and the dotted line refers to yearly responses.

In addition, we can see that the effect of housing prices on real estate development loans was also stronger than the effect in the opposite direction.

6. Conclusions

The limitation of the VAR model is that it cannot capture possible non-linearity or time variation in the lag structure of the model, and it also cannot capture possible heteroscedasticity of the shocks and non-linearity in the simultaneous relations among the variables of the model. Meanwhile, the TVP-VAR model with stochastic volatility is so flexible and robust that it can capture possible changes in the underlying structure of the economy. For this reason, in accordance with following Nakajima (2011), we used the TVP-VAR model with stochastic volatility to study the dynamic relationship between bank credit and housing prices in China from 2005Q2 to 2007Q4. Moreover, in order to study how bank credit affects buyers and developers, we also performed the same estimation for housing loans and real estate development loans. Finally, we obtained the following findings.

Firstly, the relationships between housing prices, bank credit, housing loans, and real estate development loans showed significant time-varying features, meaning that they change in different periods.

Secondly, the mutual effect between housing prices and bank credit varied between the different sides. In the market as a whole, the mutual effect over the whole sample period in China was shown to be positive. On the demand side, the mutual effect between housing prices and housing loans was also positive in most measured periods. However, we still saw that the effect of housing loans on housing prices for each quarter was negative in some years which casts doubt on the controllability of the housing loans control channel which is intended to control housing prices in the short term. On the demand side, the effect of housing prices was shown to be negative which seems to not coincide with the theoretical analysis in Section 2, but there is a possibility that is influenced by government regulation. In the opposite direction, the effect of real estate development loans on housing prices was shown to be negative in the long term, half-year and yearly periods, but positive for the short-term, quarterly, and some yearly periods, which coincides with the theoretical analysis.

Finally, it is also interesting to note that influences of housing prices on all kinds of bank credit are stronger than those in the opposite direction. This implies that the People's Bank of China should pay attention to the risk that a housing price collapse would have effects on the bank credit system.

Based on the TVP-VAR with stochastic volatility, we identified the time-varying effects of bank credit on housing prices and the reverse in the Chinese housing market. Furthermore, we found different time-varying relationships between these two factors on the demand side and the supply side. Nevertheless, we did not find evidence of, or observe, any reasons why a time-varying effect happened during this period. This could be a future study direction.

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