https://doi.org/10.26599/IJCS.2022.9100006 International Journal of Crowd Science

Credit Policy and Housing Market Liquidity: An Empirical Study in Beijing Based on the TVP-VAR Model

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ABSTRACT

Although there is a consensus that the housing market is deeply affected by credit policies, little research is available on the impact of credit policies on housing market liquidity. Moreover, housing market liquidity is not scientifically quantified and monitored in China. To improve the government's intelligence in monitoring the fluctuation of the housing market and make more efficient policies in time, the dynamic relationship between credit policy and housing liquidity needs to be understood fully. On the basis of second-hand housing transaction data in Beijing from 2013 to 2018, this paper uses a time-varying parameter vector autoregressive model and reveals several important results. First, loosening credit policies improves the housing market liquidity, whereas credit tightening reduces the housing market liquidity. Second, both the direction and the duration of the impacts are time-varying and sensitive to the market conditions; when the housing market is downward, the effect of a loose credit policy to improve market liquidity is weak, and when the housing market is upward, market liquidity is more sensitive to monetary policy. Finally, the housing market confidence serves as an intermediary between credit policy and housing market liquidity. These results are of great significance to improve the intelligence and efficiency of the government in monitoring and regulating the housing market. Several policy recommendations are discussed to regulate the housing market and to stabilize market expectations.

KEYWORDS

housing market liquidity; credit policy; Time On Market (TOM); Time-Varying Parameter Vector AutoRegressive (TVP-VAR) model

Since the housing reform in 1998, China's housing market has grown rapidly with the acceleration of urbanization. Before the global financial crisis in 2008, China's urban housing market experienced a golden period of development. Since then, China's housing market has fluctuated violently. As an important part of China's market economy system, the healthy and stable development of the housing market is critical to people's livelihood. Therefore, the housing market is a market that is heavily regulated by policies, and the direction of regulation changes according to the market conditions, forming a regulation cycle of "shrinking-expansion-shrinking-expansion"[1].

Housing credit policy plays an important role in housing regulation. Loose credit policies helped China's housing market recover from the 2008 global economic crisis quickly. Since 2010, a relatively strict housing credit policy has been adopted, especially for the purchase of second houses. Both the minimum down payment requirement and the loan rate for buying a second home or more homes have been raised significantly. With the downward pressure of China's economy in 2014, the growth of the housing market slowed down and showed a trend of oversupply. The target of housing market regulation was adjusted accordingly to stabilize growth and destock housing. Most cities canceled housing purchase restrictions and reduced the deed tax. On September 30, 2015, the down payment ratio was reduced. Subsequently, housing prices increased rapidly across the country, especially in first- and second-tier cities. In December 2015, the price of newly built commercial housing in 70 large and medium-sized cities increased by 7.7% compared with that in the previous December. The growth rate of housing prices in the four first-tier cities was significantly higher than that in other cities. Shenzhen was the city with the largest increase in housing prices, experiencing a 47.5% increase, and the growth rates of housing prices in Shanghai, Beijing, and Guangzhou were 18.2%, 10.4%, and 9.2%, respectively. On September 30, 2016, a large number of tightening real estate policies were introduced, which were tightened further on March 17, 2017. Currently, the housing credit policy still maintains its strictest level in major Chinese cities. In Beijing, for example, the down payment requirement is as high as 80%, and the interest rate for a second home loan is 120% of the benchmark.

The impact of credit policies on the housing market has always been a hot topic of research. The prosperity of the housing market is generally believed to be usually accompanied by the expansion of credit, and the low cost of credit or easy credit availability will accelerate the rise of housing prices[2,3]. The low cost of mortgage brought by the expansion of bank credit will increase household mortgage demand and increase the household's liquidity premium[4–6]. Meanwhile, loose credit policies and market prosperity have attracted capital to be over-allocated to the housing development, further stimulated household housing consumption, and are also an important reason for the increase in housing prices[7–9]. Moreover, the long-term low interest rate will cause a real estate market bubble[10,11]. Generally, the existing research focuses on the impacts of credit policy on housing prices and housing development.

The impact of credit policies on the housing market liquidity has been less explored. This neglect is mainly due to data limitations. First, the data and quantitative methods about the

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housing market liquidity are not as readily available as housing prices. Second, the factors that affect the liquidity of the housing market are complex, and the availability of data on these factors is a challenge. However, market liquidity plays an equally important role in the housing market as housing prices. Moreover, changes in market liquidity often precede changes in housing prices. Therefore, to improve the understanding of the dynamic relationship between credit policy and housing market liquidity, a smarter approach is needed to overcome the difficulty in data availability.

The aim of this research is to reveal the impact of credit policy on housing market liquidity and its mechanism. First, by reviewing economic theory and existing research results, we theoretically elaborate on the transmission mechanism of the influence of credit policy tools on housing market liquidity. Then, using the data on second-hand housing transactions in Beijing, we empirically study the impact of credit policies on housing liquidity and conduct an in-depth analysis of the time-varying nature of this impact. Next, we explore the intermediary role of market confidence in the impact of credit policies, approached by the Baidu Heat Index. Finally, we propose policy recommendations to improve the accuracy and effectiveness of housing market regulations from the perspective of improving the liquidity of the housing market. The significance of this study is self-evident. First, through a more scientific and smarter model called the Time-Varying Parameter Vector AutoRegressive (TVP-VAR) model, the role of credit policy is evaluated comprehensively and scientifically. Second, the results of this study provide valid supportive evidence for the government to monitor the fluctuation of the housing market and to create more effective policies in time.

This paper proceeds as follows. The current research on housing liquidity, credit policy, and the relationship between them are reviewed in Section 1. Section 2 provides a theoretical discussion of the impact of credit policies on housing market liquidity and its mechanism. Section 3 describes our data and presents summary statistics. Section 4 presents our empirical strategies and discusses the empirical results. Section 5 concludes by summarizing the results and policy implications.

1 Related Literature

This research is related to two branches of research. One is the study on housing market liquidity, and the other is the study on the impact of credit policies on the housing market.

The importance of housing market liquidity has been acknowledged by the literature for a long time[12–15]. How to measure the liquidity of the housing market is one of the main problems faced by related research. Housing liquidity is the ease at which assets can be traded[13]. Some scholars believed that the absolute value of market transaction volume can directly act as a proxy for the housing market liquidity[16,17]. A more widely used approach defines the housing market liquidity as time on the market, that is, " the optimum expected duration of asset realization determined by the optimal seller search strategy"[18,19]. Empirically, many studies use the average sales duration of housing units sold in a fixed time interval to approach the housing market liquidity during this period. Compared with the fluctuation of housing prices, the market liquidity presents greater volatility. Liquidity is believed to be a true reflection of the situation of the housing market[20–22].

A review by Wu et al.[23] summarized the influencing factors of housing market liquidity into two groups: micro and macro factors. From the micro aspect, the characteristics of a housing unit affect its specialization and popularity in the market, which ultimately manifests in the difference in liquidity in the housing market. For example, the liquidity of older houses with old structures, superior geographic locations, and high land premium is generally lower than the average market liquidity[24]. The air, noise and other pollution in the neighborhood or major public incidents nearby will not only reduce the housing prices but also slow down the speed of transactions[25,26]; The building technologies adopted[27], the available public services[28], and the surrounding industrial types[29]also affect the transaction process. From the macro perspective, fluctuations in housing liquidity are related to economic conditions[30] and are co-moving with credit policies.

Adjustments in the interest rate and credit amount directly affect the financing costs of home buyers and real estate developers, thereby affecting the housing demand and supply and resulting in fluctuations in market transactions[31,32]. Specifically, when the credit policy is tightened, both the construction volume of the new houses and the transaction volume of second houses decline rapidly. When the credit policy is loose, the expected capital gains formed in the market drive up the housing demand, and credit abundance has a strong positive effect on market prosperity[33,34]. Xiao and Devaney[34] research on the housing market in London, Lyons[35] research on Ireland, and Maggio & Kermani[36] research on the United States all provided supportive evidence that a loose credit policy is associated with an increase in house prices. On the basis of financial data from 20 countries, Anundsen et al.[37] believed that abundant credit brings high leverage to households and enterprises, resulting in housing price bubbles and increasing the possibility of the bubble bursting. Despite abundant studies on the effects of credit policies on housing prices, studies on the influence of credit policy on the housing market liquidity are limited. Few studies based on the housing market in the United States, Finland, and Italy provide supportive evidence for the impacts of credit policies on the liquidity of the housing market[22,38,39].

With the development of China's housing market, housing credit amounts have continued to expand, the interest rate of housing loans has generally declined, and the supply and demand of housing have changed accordingly[40]. Most of the funds flowing in China's housing market come from bank loans[41], so the impact of credit control policies on real estate is effective. Housing prices are closely related to the availability of credit and the scale of housing consumption loans[42–44]. The increase in loan interest rates reduces the market demand, leading to an inverse relationship between the interest rate and housing price[45]. Pan[46] divided China's housing price fluctuations into two ranges: large and small, and built an MS-VAR model based on the data from 2005 to 2017 to explore the asymmetric impact of credit on housing prices, the results showed that the increase of loans will lead to the rise of housing prices, the tightening of policies and the increase of interest rates will lead to the decline of housing prices, which is consistent with the view of Su et al.[47]. Some scholars obtained the opposite result. Kuang[48] used the real mortgage interest rates of 35 large cities from 1996 to 2007 and found that the tightening of the central bank's interest rate cannot restrain housing prices but instead lead to an increase in current housing prices.

However, the impacts of credit policy on the housing market liquidity in China have been less explored. This gap is what this research aims to fill.

2 Theoretical Hypotheses

Credit tools including interest rates and loan amount are widely used to regulate the housing market. The cost and capacity of construction loan of the developers and the cost and capacity of mortgage loan of households determine the relationship between supply and demand in the housing market[49]. The control measures for the developer include the interest rate of construction loans, restrictions on loan approval, and financial leverage. Control measures for the home buyers include the interest rate of the mortgage, the minimum down payment ratio, the maximum loan period, and the maximum loan amount.

The influence mechanism of the above credit tools on the housing market liquidity is shown in Fig. 1 . When the government loosens credit policies, interest rates decrease and loan volume increases. Then, loan cost decreases and loan capacity increases for both developers and home buyers. The investment in housing development and the purchasing power of the households are driven up, and both housing supply and demand increase, resulting in a boom in the housing market and an increase in transactions. Therefore, a loose credit policy improves the housing market liquidity. According to the same logic, a tight credit policy reduces the housing market liquidity.

On the basis of the above analysis, we propose the following theoretical hypotheses:

Hypothesis 1: Housing market liquidity responds to the shock of the scale of credit positively.

Hypothesis 2: Housing market liquidity responds to the shock of the interest rate negatively.

The housing market is a market with transaction frictions; therefore, the transaction speed of housing and thus the market's liquidity is affected not only by the supply and demand determined by macro market conditions but also by transaction frictions at the micro-level. The housing searching and matching model shows that the seller gives a listing price according to the expectations of the housing market. Meanwhile, he forms a reservation price that is the lowest price accepted, thus forming an acceptable price range. Only when the buyer's asking price falls within this range can the buyer and seller match, leading to a transaction.

A consequent question is how people form expectations about the housing market. The interactions between objective macroeconomic conditions and subjective consciousness lead to the formation and change of market expectation. In the face of a complex and uncertain environment, the adjustment of relevant policies provides a strong signal to market participants that they will adjust market expectations according to the direction of policy adjustment and change their confidence in the market. Therefore, credit policy will also affect the probability of match by influencing the market expectations of buyers and sellers, which in turn affects the liquidity of the housing market.

As shown in Fig. 1, when credit expands, the expectation of a boom in the housing market increases the market confidence of participants. Sellers will increase the listing price while the reservation price remains unchanged. The acceptable price range of the seller will increase, and buyers will offer a price more frequently. The reduction in transaction frictions makes reaching a transaction easier for both parties, and the level of market liquidity improves as a result. In contrast, tight credit policies reduce market confidence and increase market frictions during a housing transaction, thereby reducing the housing market liquidity. Therefore, we propose the third hypothesis.

Hypothesis 3: Market confidence plays an intermediary role in the impact of credit policies on the housing market liquidity.

3 Date and Summary Statistics

Several different ways can be used to measure the housing market liquidity, including the rate of sale[50,51], Time On Market (TOM)[22,52], and the number of transactions[16]. TOM is the most widely used one and is applied in this study. TOM measures the duration of the sold housing unit in the market, that is, the time interval between the listing date and the sale date of the housing unit. Strong market liquidity corresponds to short TOM.

To construct the variable of TOM, we apply the resale housing transaction data between 2013 and 2018 from Beijing. To improve the accuracy and representativeness of quantitative measure of the market liquidity, we first delete abnormal observations, including the transaction records where the price per square meter is less than 1000 RMB, the construction area exceeds 350 square meters, or the property has been listed for more than three years. Then, following the method in Eerola and Määttänen[22], we take the transaction date of the unit as the reference time point to calculate the *TOM* of the housing unit. The average value of the *TOM* of all units sold in a month is the monthly *TOM*. Mathematically, the monthly housing market liquidity level is calculated as follows:

$$TOM_i = \frac{\sum_{t=1}^{m}(Date_{sale_t} - Date_{list_t})}{m}, \quad Date_{sale_t} \in i,$$

where m is the number of housing units sold in month i.

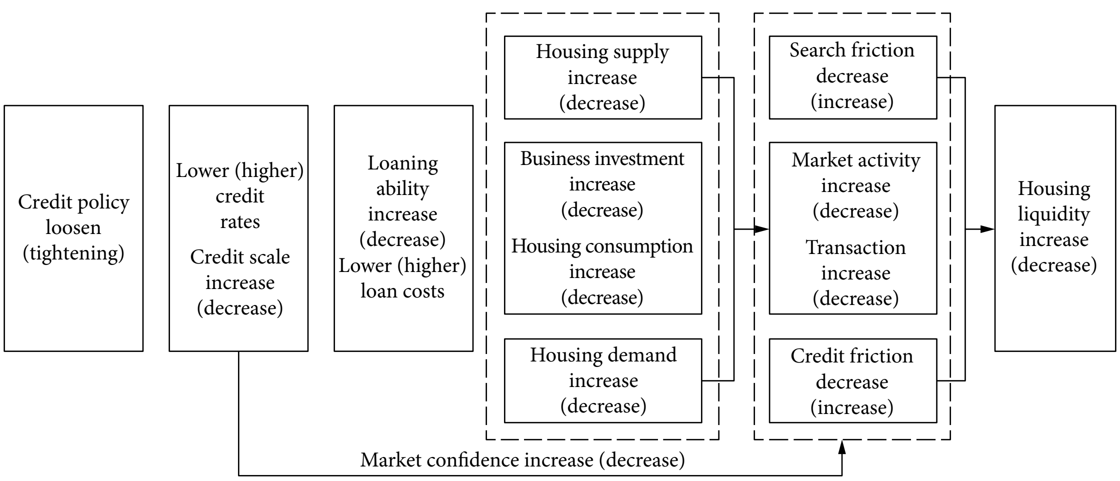


Fig. 1 Influencing mechanisms of credit policy on housing market liquidity.

Two instruments are applied to represent the credit policy: the credit quota and the interest rate. The credit quota is measured by the monthly change rate of the consumption loans balance in Beijing, denoted by *Change_rate*. This approach is taken because of two reasons. First, medium- and long-term consumption loans can well represent housing loans because most consumption loans are mortgage loans, except for a very small proportion of loans for car consumption and luxury goods consumption. Second, because data on monthly new mortgages issued are not available, the monthly change rate of consumption loans balance from the financial institutions in Beijing is used instead. The benchmark interest rate for the five-year loan announced by the central bank, denoted as *Loan_int*, is used to measure the interest rate in Beijing's housing market. The rate is an interest rate that has a universal reference role in China's financial market. Residential mortgage rates are adjusted based on this rate. The benchmark interest rate is an important tool for the central bank to stabilize the market. When the market is booming, the interest rate will increase in a timely manner to curb overheated demand; when the market is down, it will decline.

In the study of behavioral economics, the public's attention to the market generally represents their confidence in the market. Strong market confidence corresponds to greater attention to the market and a higher frequency of keywords related to the market in online searches[53,54]. Therefore, the search frequency of keywords related to the housing market over a period of time can be used to represent the confidence in the housing market during that period. The variable of housing market confidence in this research, which is denoted as *Index*, is constructed via the Baidu index by selecting "second-hand housing", "house price", and "real estate" as the keywords for the housing market. The Baidu index is constructed based on the search frequency of these three keywords. Min-max normalization is applied to normalize the Baidu index to the *Index* with values ranging from 1 to 100.

Table 1 introduces the definitions of all the variables and reports their summary statistics, and Fig. 2 shows the time trends of these variables during the study period. As shown in Table 1, the average *TOM* between 2013 and 2018 was 71.56 days, the monthly growth rate of the consumption loan was 15.45%, the interest rate was 5.53%, and the index of the housing market confidence was 42.53. Figure 2 shows that the variation of the *TOM* is significant, thereby suggesting that housing market liquidity experiences fluctuation during the study period. Generally, the *TOM* moves inversely with *Chang_rate* and *Index*. Although interest rates lowered from late 2014 to late 2015 only, that period also coincided with a rapid decline in the *TOM*. These facts support our hypotheses about the relationships among credit policy, housing market liquidity, and market confidence.

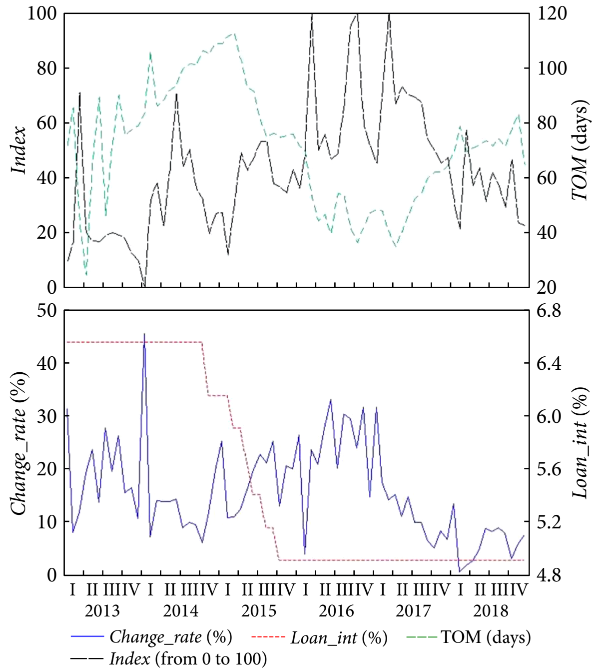


Fig. 2 Time series trend of *Change_rate*, *TOM*, *Index*, and *Loan_int*. Ⅰ, Ⅱ, Ⅲ, and Ⅳ represent four quarters of the years.

4 Empirical Analyses

4.1 Econometric model

This study uses a TVP-VAR model to study the dynamic relationships between the housing market liquidity and credit policies. The VAR model is used to describe the dynamic relationship between the variables that affect each other[55]. However, the traditional VAR model assumes that the variance of the coefficients and random disturbance terms are fixed. In fact, the interrelationships between variables are time-varying and nonlinear because the macroeconomic environment is constantly changing. This idea implies that the parameters of the VAR model are constantly changing, thus leading to the inability of the traditional VAR model to explain the long-term dynamic relationship between variables. Therefore, Primiceri[56] extended the model to a TVP-VAR model, which assumes that parameters, such as coefficients, variances, and covariances, are time-varying, and makes it more suitable for studying macroeconomic problems that have strong uncertainty. The specific form of the model is as follows:

$$Y_t = X_t\beta_t + A_t^{-1}\sum\nolimits_t \mu_t,\ t = s+1, s+2, \ldots, s+h,$$

where Y_t is a vector ($h\times 1$) of observed dependent variables and X_t is a matrix ($h\times k$), including intercepts and lags of the endogenous variables. In one equation of the model with dependent variable y_t, which represents *TOM*, other variables, including *Change_rate*, *Loan_int*, *Index*, and the lags of all the variables, are placed in the vector ($1\times k$) of x_t. Coefficient vector β_t, parameter matrices A_t^{-1}, and $\sum_t \mu_t$ all vary with time. When the coefficients and parameters are time-varying, the computational complexity of the estimation model also increases. The traditional likelihood estimation method has difficulty estimating all the parameters accurately.

Table 1 Variable definitions and statistics.

Variable	Definition	Obseruation	Mean	Standard deviation	Min	Max
TOM (days)	Time on the market	72	71.56	21.76	10.55	112.59
Change_rate (%)	Monthly change rate of the balance of consumption loans	72	15.45	9.03	0.32	45.36
Loan_int (%)	Interest rate for the five-year loan	72	5.53	0.76	4.90	6.55
Index	Index of the housing market confidence	72	42.53	22.30	0	100

Therefore, the Markov Chain Monte Carlo (MCMC) estimation method based on the Bayesian framework was developed by Nakajima[57] to improve the accuracy and speed of the estimation. The MCMC estimation has advantages in the nonlinear likelihood function under the random fluctuation setting, thereby improving the accuracy and estimation speed of the estimation results in the TVP-VAR model.

The TVP-VAR model, which is extended from the traditional VAR model, also requires the variables to be stable. If the variables are not stable, then a fake regression phenomenon will occur. ADF stability tests are conducted for all the time series variables applied in this study, and the results are reported in Table 2. The series of *TOM* is initially unstable and then stabilizes after the first-order difference (*DTOM*). The other three variables all tend to be stable.

Following the setting of the TVP-VAR model by Wu and Fu[58], the first- and second-order lags of the variables are included according to the information criterion in the VAR model, and the number of iterations of MCMC estimation is set to 10 000 times. The model is unstable in the early stage of estimation. Thus, the results of the first 1 000 times are discarded to improve the accuracy of model estimation. Table 3 presents the estimation results of the TVP-VAR model.

4.2 Impulse response functions of TOM to credit policy

The TVP-VAR model assumes that the parameters are time-varying; thus, the time-varying Impulse Response Functions (IRF) of each variable should be calculated. There are two types of IRF: equidistant and time-point IRF. The former function illustrates the changes of the dependent variable after equal time intervals, caused by a positive shock of one standard deviation in an independent variable at each time point. The latter function can be used to investigate the attenuation of the impact of the dependent variable over time caused by a positive shock of one standard deviation in an independent variable at a specified time point.

In this study, three time intervals of 1 month, 6 months, and 12 months are selected as the intervals of the equidistant IRF and represent the short-term, mid-term, and long-term impulse response effects, respectively. The time nodes of the time-point IRF include September 30, 2014, September 30, 2015, September 30, 2016, and March 17, 2017, which are four policy adjustment time nodes during the sample period. As described in the introduction section, the former two are the time nodes for the easing and further easing of housing credit policies, while the latter two are the time nodes for the tightening and further tightening of housing credit policies.

Impulse response of *DTOM* to *Chang_rate*: Figure 3a is the equidistant impulse responses of the housing market liquidity (*DTOM*) to the credit scale (*Chang_rate*). The dotted, dashed, and solid lines represent the impulse responses with time intervals of 1 month, 6 months, and 12 months, respectively. The results show that a positive shock of one standard deviation to *Change_rate* has a significant impact on the change of *TOM* , but significant differences exist in the magnitude, direction, and dynamic trend of the impulse responses.

The direction of the impulse response with an interval of 1 month is positive and stable at 1 unit. The impulse response with an interval of 6 months is the strongest, fluctuating between −3 and −4 units. The impulse response with an interval of 12 months is −3 units initially, which then increases to positive, and finally decreases to −3 units again. When a loosening signal of credit volume is released, the liquidity of the housing market does not improve in the short term, possibly because reaching a housing transaction takes time and thus, liquidity will not fluctuate violently in the short term. Meanwhile, most market participants adopt a wait-and-see strategy in the short term, leading to a lag effect in the implementation of policies. In the medium and long terms, when the credit scale increases by one standard deviation, *TOM* decreases by 3 to 4 units. A loose credit policy will significantly improve the speed of housing transactions, thereby increasing market liquidity.

Figure 3b is the time-point impulse responses of the housing market liquidity (*DTOM*) to the credit scale (*Chang_rate*). The dotted and dashed lines respectively represent the time points in 2014 and 2015 when the market was downward and the credit policy was loose. The solid and dotted-dashed lines respectively represent the time points in 2016 and 2017 when the market was upward and the credit policy was tightened. First, when the credit volume expands by one standard deviation, *TOM* rises and the

Table 2 Results of ADF tests for all time series variables.

Variable	(C, T, K)	DW	ADF	*t*-statistic critical value			Stability
				10%	5%	1%	
TOM	(C, n, 0)	2.085	−2.433	−2.589	−2.904	−3.527	FALSE
DTOM	(n, n, 0)	1.876	−9.646	−1.614	−1.946	−2.599	TRUE
Change_rate	(C, T, 0)	2.091	−6.239	−3.164	−3.474	−4.093	TRUE
Loan_int	(n, n, 0)	2.035	−2.386	−1.614	−1.946	−2.598	TRUE
Index	(C, T, 0)	2.085	−4.190	−3.164	−3.474	−4.093	TRUE

Table 3 Estimation results of TVP-VAR model.

Parameter	Mean	Standard deviation	Upper quantile	Lower quantile	Geweke	Inef.
$(\Sigma_\beta)_1$	0.0023	0.0003	0.0018	0.0029	0.221	5.19
$(\Sigma_\beta)_2$	0.0023	0.0003	0.0018	0.0029	0.188	5.81
$(\Sigma_\alpha)_1$	0.0057	0.0018	0.0034	0.0103	0.515	29.88
$(\Sigma_\alpha)_2$	0.0051	0.0023	0.0033	0.0077	0.737	17.24
$(\Sigma_h)_1$	0.2637	0.0936	0.1196	0.4764	0.739	43.91
$(\Sigma_h)_2$	0.0058	0.0017	0.0035	0.0103	0.961	26.21

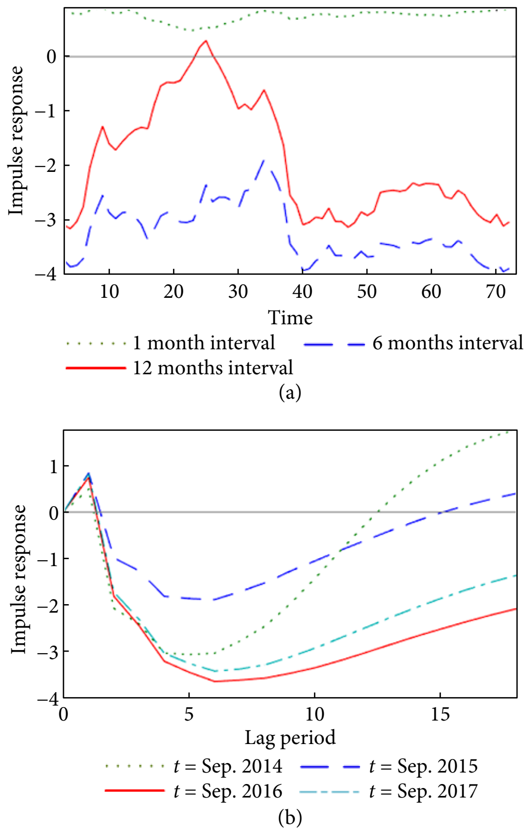


Fig. 3 Equidistant (a) and time-point (b) impulse responses of *DTOM* to *Change_rate*.

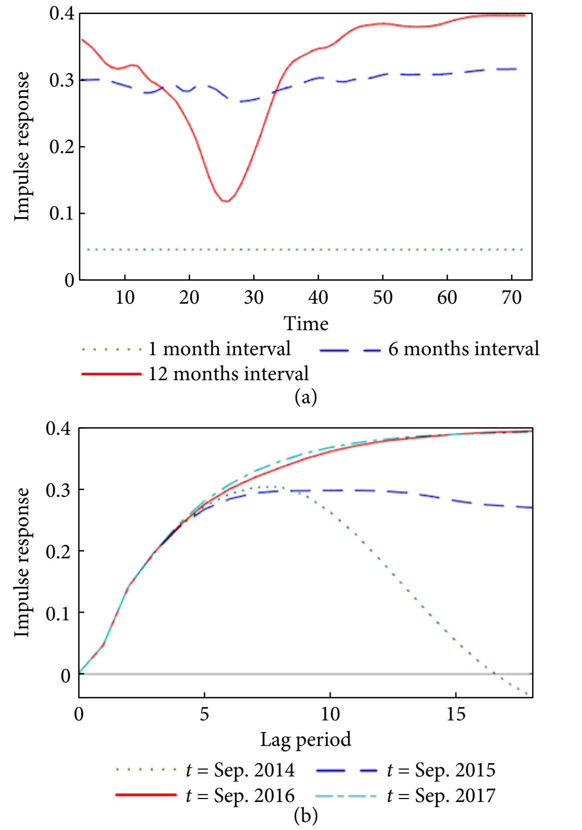


Fig. 4 Equidistant (a) and time-point (b) impulse responses of *DTOM* to *Loan_int*.

market liquidity reduces in the short term (about one month). This situation again suggests that market participants adopt a wait-and-see strategy in the early stage of credit policy adjustment, and the role of the policy has a lagging effect. Second, increasing the scale of credit reduces *TOM*, thereby increasing the housing market liquidity. Moreover, the magnitude and trend of the effect vary with market conditions. Specifically, when the market is in a depression stage, the effect of reducing *TOM* by increasing the credit scale is less and does not last long. When the credit scale increases by one standard deviation, the decrease in *TOM* reaches the maximum magnitude of 3 units in 5 months and then gradually increases. After around one year, *TOM* returns to the original level. When the market is in the expansion stage, the effect of reducing *TOM* by increasing the credit scale is large and the duration is long. When the credit scale increases by one standard deviation, *TOM* drops rapidly, with a maximum drop of 4 units. After 20 months, this negative impact remains at 2 to 3 units.

Figure 4a is the equidistant impulse responses of the housing market liquidity (*DTOM*) to the interest rate of housing loan (*Loan_int*). The dotted, dashed, and solid lines represent the impulse responses with time intervals of 1 month, 6 months, and 12 months, respectively. The results show that increasing the interest rate by one standard deviation has a significantly positive impact on the change of *TOM*, and the magnitude and trend of time-varying of the impulse responses vary by different time intervals.

The impulse response of *DTOM* with an interval of 1 month is very small and stable. Therefore, in the short run, market liquidity is not sensitive to changes in interest rates. However, in the medium and long terms, market liquidity is very sensitive to changes in interest rates. The impulse response of *DTOM* to *Loan_rate* is stable at around 0.3 unit. The long-term impact of credit rates on housing market liquidity first falls, then rises, and finally stabilizes at a higher level.

Figure 4b is the time-point impulse responses of the housing market liquidity (*DTOM*) to the interest rate (*Loan_int*). Parallel to Fig. 3b, the dotted and dashed lines represent the time points in 2014 and 2015, respectively, and the solid and dotted-dashed lines represent the time points in 2016 and 2017, respectively. Unlike Fig. 3, these four curves show strong consistency in magnitude and trend. Whether the market is in recession or inflation, higher interest rates can increase *TOM*, thereby reducing the housing market liquidity. This inhibitory effect on market liquidity continues to increase over time. The only exception is the impulse response for the time point of September 30, 2014. At that time point, after a positive shock in the interest rate, a positive spillover effect occurs on *TOM*, and the impact of the shock on *TOM* peaks in the ninth period and then begins to decay gradually to zero after 15 periods. This result might have occurred because some additive effects cannot be isolated in our model.

Overall, the above analysis shows that credit scale and interest rates can significantly affect the liquidity of the housing market, and these effects present time-varying trends and have a lagging effect. Therefore, theoretical Hypotheses 1 and 2 are validated. Moreover, compared with the credit volume, the impacts of interest rates on the housing market liquidity are more consistent and stable and are less sensitive to market conditions.

4.3 Role of market confidence

To test theoretical Hypothesis 3, whether market confidence plays an intermediary role in the impact of credit policies on the housing market liquidity, we first analyze how market confidence responds to credit policy adjustments and then show how the market liquidity responds to market confidence changes.

4.3.1 Impulse response of *Index* to *Chang_rate* and *Loan_int*

Figure 5 illustrates the results of impulse response of market confidence (*Index*) to the credit scale (*Chang_rate*). Here, Figs. 5a and 5b are the equidistant and time-point impulse responses, respectively. Compared with the impact of *Change_rate* on *TOM* in Fig. 3, the impact of changes in credit scale on market confidence has a structural difference, and both the direction and magnitude of the impact are time-varying. When the credit scale increases by one standard deviation, the short-term impact on the market confidence index is negative, but the magnitude is very small. The impulse responses of *Index* with 6-month and 12-month intervals are negative for 35 time periods; then they become positive afterward. This result implies that loosening credit supply can increase the medium- and long-run market confidence only in the second half of the study period, which is after 2016. The time-point responses of *Index* to *Chang_rate* suggest that the impacts of credit volume on market confidence depend on the market conditions. When the housing market is downward, an increase in the credit supply does not help increase the market confidence; as a matter of fact, market confidence falls further. When the housing market is upward, an increase in the credit supply drives up the market confidence further.

The results in Fig. 6, which show the impulse response of *Index* to *Loan_int*, again suggest that the interest rate is a better tool than the credit scale for regulating the housing market. The interest rate for housing loans increases by one standard deviation, and short-, medium-, and long-term market confidence all decline. This negative effect on market confidence continues to increase over

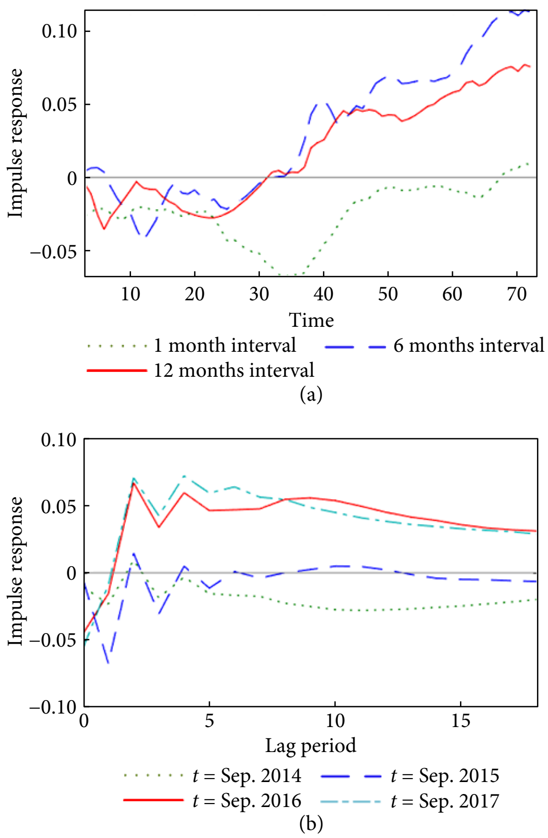


Fig. 5 Equidistant (a) and time-point (b) impulse responses of *Index* to *Chang_rate*.

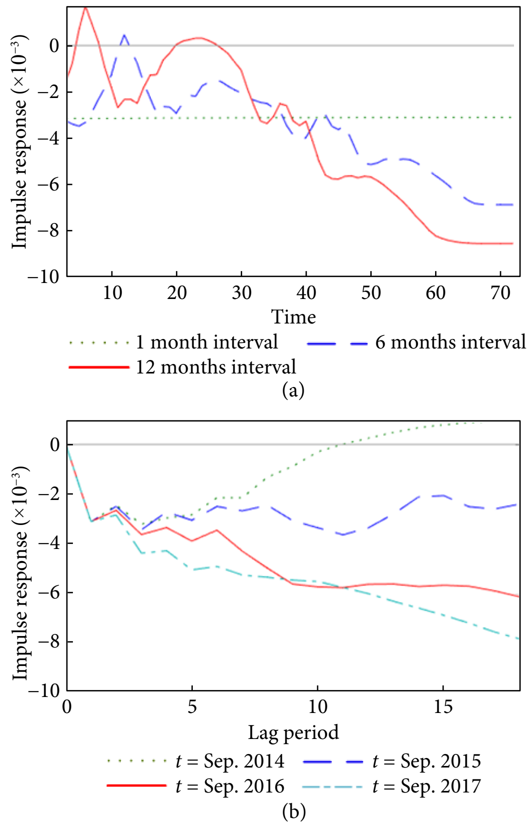


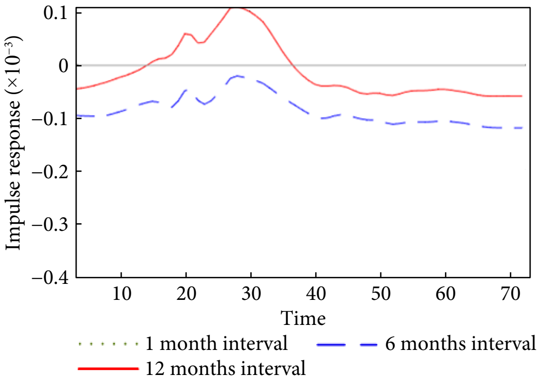
Fig. 6 Equidistant (a) and time-point (b) impulse responses of *Index* to *Loan_int*.

time. Moreover, higher interest rates reduce the market confidence regardless of the market conditions, as suggested by Fig. 6b. *Index* responds to a positive shock of *Loan_int* negatively for all four time points, although these responses exhibit different time-varying trends.

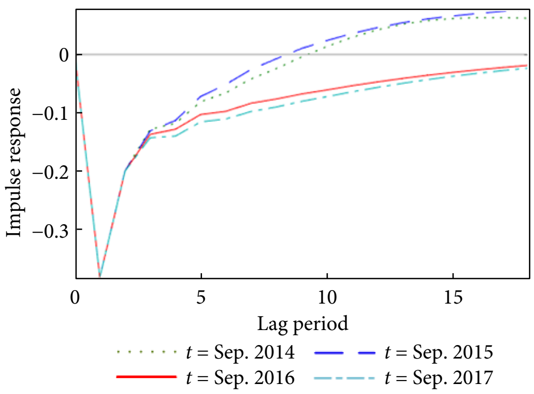
4.3.2 Impulse response of *DTOM* to *Index*

Figure 7 shows how the market liquidity (*DTOM*) responds to a positive shock of one standard deviation in market confidence (*Index*). Figure 7a shows the equidistant impulse responses. The results show that the changes in *DTOM* response to *Index* with an interval of 1 month close to −0.5 units and are very stable during the study period, suggesting that market liquidity is sensitive to changes in market confidence. The negative responses of *DTOM* to *Index* become smaller when the time interval becomes longer. After market confidence increases by one standard deviation, the decline in *TOM* is around 0.1 unit. Figure 7b shows the impact of *Index* on *DTOM* at different time points. The directions of the impact are consistent, and the magnitudes are time-varying. Market confidence played a significant role in improving market liquidity during the first three months, and the effect lasted longer at the time points in 2016 and 2017 when the market was upward than that in 2014 and 2015 when the market was downward.

A summary of the results in Figs. 5–7 shows that with loose credit policies, increased credit scale, or reduced loan interest rates, market participants increase their confidence in the market and speed up their housing transactions, thus improving the housing market liquidity. Therefore, in the process of using the credit policy to regulate the liquidity of the housing market, market confidence plays an intermediary role.



(a)



(b)

Fig. 7 Equidistant (a) and time-point (b) impulse responses of *DTOM* to *Index*.

5 Conclusion and Policy Recommendations

By constructing the housing market liquidity index *TOM* based on the microtransaction data of second-hand housing in Beijing from 2013 to 2018, this study establishes the TVP-VAR model to explore the dynamic relationships between credit policy and housing market liquidity. Three important results are revealed. First, increasing the credit supply and reducing the loan interest help reduce the duration of housing in the market, thus improving the housing market liquidity. However, lagging effects exist. Second, the patterns of time-varying impacts of the credit tools are asymmetric and depend on the housing market conditions. In general, compared with the control of the credit amount, the impact of interest rates on housing market liquidity is more efficient, and all these effects in the upward market are stronger than those in the downward market. Third, market confidence plays an intermediary role in the policy effect.

This paper contributes to the existing research in two ways. First, new empirical evidence of the significant and time-varying impacts of the credit volume and interest rate on housing market liquidity enrich the evaluation of credit policies. This finding also provides a valuable reference that can enable the government to adjust policies in a timely manner. Second, the research method is improved in this study. The TVP-VAR model is able to describe the dynamic relationship between the tools of credit policy and the housing market liquidity with limited data.

The findings of this study have important policy implications for improving the accuracy, effectiveness, and efficiency of housing credit policy. First, a dynamic housing liquidity index database needs to be established to improve the government's monitoring and regulating system for the housing market. Second, in terms of consistency and stability of the impacts on the housing market liquidity, the interest rate is a better tool than the credit scale. Therefore, the tool of interest rate is more recommended for regulating the housing market. Third, the lagged effect makes the medium- and long-term impacts of policies more significant, so the policy needs to be consistent to avoid market disturbance caused by frequent adjustments. The timing of the introduction of new policies is also crucial. Last but not least, attention needs to be paid to the intermediary role of market confidence, which is necessary to guide market participants in forming reasonable market expectations.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. NSFC71804206).

Dates

Received: 6 January 2022; Revised: 2 March 2022; Accepted: 2 March 2022

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