Measures of mortgage default risk and local house price dynamics

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Abstract

Following the financial crisis, a voluminous literature has developed that aims to shed light on the endogenous relationship between mortgage default risk and house prices. In this paper we contribute to this literature by using measures of mortgage default risk reflecting different stages of the household default decision: from early online searches to actual default, to the resale of the foreclosed home. We use a Panel Vector Autoregressive (PVAR) model to examine the impact of these default risk measures on two segments of residential real estate markets (top and bottom price tiers) from 92 metropolitan areas in 25 US states. We find that the default risk derived from households' Google searches has the strongest negative impact on high value homes while the percentage of home foreclosed and the foreclosure resales have the strongest negative impact on the prices of low value homes. These results hold for both judicial and non-judicial foreclosure states as well as 'recourse' states. In 'non-recourse' states the number of homes foreclosed has the strongest negative impact on high value homes, which we interpret as evidence in support of the "double trigger hypothesis." That is, households default not only because they are in financial distress but also because they end up with a negative equity in their homes considering current house prices.

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1. Introduction

The housing market boom and boost of the past decade and the subprime mortgage crisis have demonstrated that the financial decisions of homeowners are of primary importance to the stability of the financial system and the macroecomy. Following the financial crisis, a voluminous literature has developed that aims to better understand the nature on one of the key interdependencies that contributed to the crisis: the endogenous relationship between rising mortgage default rates and downward spiraling house prices. Indeed, the nexus between house prices and foreclosures has been the focus of two distinct strands of literature. The one strand of this literature examines the time series interdependence between aggregate house price indices and foreclosure rates by relying on aggregate indices to capture house price dynamics (see, e.g. Calomiris, Longhofer and Miles, 2013; Garedi et. al., 2015; Mian et. al.; 2015). The other strand uses transaction data on individual residential properties to examine the effect of foreclosures or other types of forced sales on prices (Anenberg and Kung, 2014; Campbell, Giglio and Pathak, 2011; Gent and Kudlyak, 2011).

This paper belongs to the first strand of this literature. We add to the existing studies in three different ways. First, we use three distinct measures of mortgage default risk that cover the time span from the moment at which an individual household starts researching default options to the moment at which the home is foreclosed and sold in the market. Specifically, we use the Mortgage Default Risk Index (MDRI hereafter), proposed by Ghauvet, Gabriel and Lutz (2016), to measure the default risk originating from online Google searches. The MDRI is calculated on the basis of the information directly from mortgage borrowers and measures the concern of housing mortgage borrowers about their risk to be in default and subsequently to be foreclosed. The advantage is it can reflect the risk condition with no lags, and more importantly, give an overall reflection of the risk of home mortgages to be re-possessed and put on the market by either foreclosure procedure or non-foreclosure procedure. Further, we use the House Foreclosed and Foreclosure Re-Sales (HF and FRS hereafter) as actual default risk indicators. Compared with the MDRI, the latter two variables specifically measure the risk of home mortgages to be in default and finally end up with foreclosure.

Second, instead of using aggregate house price indices, which do not reflect the inherent dynamics of various segments of residential real estate markets, we use Zillow's tiered price indices (bottom tier and top tier) to account for the local dynamics of different price segments of the market.

Finally, we account for state characteristics such as judicial laws of foreclosures and borrower's recourse which, as previous literature has demonstrated, influences the probability of homes ending up in foreclosure proceedings (Ghent and Kudlyak, 2011; Mian, Sufi and Trebbi, 2015). According to the foreclosure and recourse laws in each state, we split the dataset into different state groups: Judicial vs. Non-Judicial states, and Recourse states vs. Non-Recourse states, analyze separately and explore the differences between each of these groups.

In this study, we report the results of a Panel vector autoregressive (PVAR) model.[1] Compared with other methodologies, the PVAR model allows interaction between different

[1] We use the code provided by Abrigo and Love (2015) to run the PVAR estimations.

endogenous variables, which is more likely to be reasonable in macroeconomy. We use Granger causal relationship test, standard impulse response function and forecast error variance decomposition function within the PVAR framework to quantify and compare the impact of default risk on tiered house value. Considering the local heterogeneity of house markets in previous literature (Glaeser et al., 2014), our study is based on metro-level data instead of state-level or country level data. The final dataset constitutes metro-level data from 92 metropolitan statistical areas in 25 states of the US during the period from January 2004 to February 2017. However, due to the limited availability of city-level data of the MDRI, we use state-level data of the MDRI as substitutions for all the metropolitan statistical areas in corresponding states.

We have found some similar findings from our empirical results compared with previous literature. Specifically, in most cases, our results confirm that mortgage default, disposed by either foreclosure procedure or non-foreclosure procedure, is the Granger cause of house prices. However, in some rare cases, it does show that the mortgage default is not the Granger cause of house prices in some subgroups when it has been measured by the MDRI or FRS. In addition, the house prices are negatively related with mortgage default. These findings are in line with the findings in the extant literature.

Next, our results also provide some interesting findings. It has been shown that, for the entire sample, the relative size of mortgage default's impact on house value will change with the varying of default risk indictors. To be more specific, in the case using the MDRI to measure mortgage default risk, the impact of default is shown to be higher on top tier house value, while it has been shown to be higher on bottom tier house value when the default risk is measured by the HF or FRS. Considering the HF and FRS only measures the risk of home mortgages to be default and end up with foreclosure, and the MDRI covers the overall default risk of home mortgages, the above difference reflects that the overall impact of mortgage default has a higher impact on top tier house value, while the risk of mortgage to be in default and end up with foreclosure has a higher impact on bottom tier house value. The latter finding is in line with the finding of Campbell, Giglio and Pathak (2011) that the foreclosure discounts are larger for houses with low-price characteristics. Further, the contrary result between using MDRI and using HF and FRS also suggest that the impact non-foreclosure disposal procedure of mortgage default has a higher impact on top tier house value.

Further, our empirical results for different state groups show that, except for the Non-recourse states, the empirical results for sub-groups are similar to that for the entire sample. Specifically, in the estimations using data from Judicial states, Non-Judicial states, and Recourse states, the default risk is shown to have a higher effect on top tier (bottom tier) house value when it's measured by the MDRI (the HF/ FRS). This is in accordance with the finding for the entire sample. However, in the estimations using data from Non-Recourse states, no matter the default risk is measured by the MDRI, HF or FRS, the effect of default risk is shown to be higher on bottom tier house value all the time, contrary with the results for the other three state groups and the non-grouped data. The contrary results between Non-Recourse states and other state groups is in line with our expectation. According to Ghent and Kudlyak (2011), it's more likely for delinquent borrowers to use foreclosure default in non-recourse states. Consequently, the overall impact of mortgage default on house value is more determined by mortgage default disposed by foreclosure procedure, making it higher on bottom tier house value.

The paper is organized as follows. Section 2 reviews existing literature on the research area about the interaction between house value and default risk. Section 3 presents the PVAR model used in our research. Section 4 describes the dataset employed. Section 5 shows our main empirical results based on the PVAR estimations. Section 6 Concludes.

2. Literature review

There have been plenty of studies on the relationship between house price and mortgage default, conducted on different data basis or focusing on different aspects of the relationship. The mechanism and size of mortgage default's impact on house prices and that of the opposite impact from house prices on mortgage default are the research topic for many studies.

Some studies are conducted in respect of the channel and size of the impact from mortgage default on house prices. Based on the individual house transaction data in Massachusetts between 1987 and 2009, Campbell, Giglio and Pathak (2011) examine the influence of forced sale on the prices of the foreclosed house itself and that of houses nearby. Specifically, the forced sale could be death-related, bankruptcy-related or foreclosure-related. According to their results, the average foreclosure-related discount is about 27 percent. Besides, the foreclosure discounts are larger for cheaper houses and larger in low-priced census tracts. The authors state that the foreclosure discounts result from vandalism of the houses, which make the houses less likely to be well maintained, and the urgent incentive of mortgage lenders to sell the houses. One thing should be mentioned is that, instead use the sale of all houses that are foreclosed as the sample, Campbell, Giglio and Pathak (2011) only categorize the sale of REO houses by mortgage lenders as a forced sale.

Similarly, using the REO listing data of individual houses from four metropolitan areas, San Francisco, Washington, DC, Chicago, and Phoenix between January 2007 and June 2009, Anenberg and Kung (2014) examine the impact of foreclosure on nearby house prices. Based on the hypothesis that house price discount centered around the REO listing date result from disamenity while that caused by competition should arise before the listing date, they estimate the impact of foreclosure on house prices over different foreclosure process periods. Their results in respect of the REO listing and non-REO listing prices before and around the listing date are in line with the hypothesis of competitive effect and disamenity effect. Besides, they also find the former effect is significant in all areas, while the latter one is only significant in low price and high density areas.

In opposite, Gerardi et al. (2015) state that the spillover effect of foreclosure on nearby house prices is the consequence of poor house maintenance, instead of supply or demand shocks in local house markets. Based on the data from 15 of the largest metropolitan areas of US, they quantify the impact of foreclosure on nearby house prices. To control for the time-invariant and time-variant unobserved factors related with house price dynamics, the authors respectively use the repeat-sale methodology from Harding et al. (2009) and triple-interaction fixed effect in the paper. According to their results, the spillover effect of house foreclosure is negative on house prices, and is related with house conditions, i.e. higher on houses with poor condition. Especially, the spillover effect is shown to be positive on houses in good condition.

Together with other findings, Gerardi et al. (2015) argue that lack of house maintenance investment, i.e. investment externality, is the cause of the foreclosure spillover effect.

Besides the mechanisms mentioned above, there is also indirectly channel through which foreclosure can influence the house prices. For example, Ellen, Lacoe and Sharygin (2013) use the data from New York City to examine the impact of house foreclosure on the criminal activity foreclosed properties affect criminal activity on the surrounding blockfaces where the foreclosure appeared. Their results show that the foreclosure increases the crime rate on the blockface on which the foreclosure occurs, and moderately increase the crime rate on nearby blockfaces. Cui and Walsh (2015) study the impact of house mortgage foreclosures and vacancies on violent and property crime, and find that the foreclosure does have a positive impact on violent crime rate. They argue that, the crime increase is driven by the vacancies caused by foreclosures, instead of the foreclosure itself. It is reasonable to predict that houses in high crime level areas tend to be lower as potential buyers are discouraged due to safety considerations.

Some other studies are more curious about the cause of mortgage default, especially the cause of foreclosure. House price declines, or subsequent negative equity of the house caused by the declines, and liquidity problem (or cash-flow problem), caused by job loss, for example, of the households, are mentioned in most studies to be the main causes of home mortgage default. The two factors are also referred as "double triggers" in the papers mentioned below (Gerardi, Shapiro and Willen, 2007; Foote, Gerardi and Willen, 2008; Bhutta, Dokko and Shan, 2010; Elul et al., 2010).

Using the loan-level data and the Case-Shiller home price index, Bajari, Chu, and Park (2008) study the factors affecting subprime borrowers' decision to default. According to their results, while borrower and loan characteristics that can affect borrowers' ability to pay, such as FICO scores and payment-to-income ratios, are also closely related with mortgage default probability, the house price decline in the nationwide is the main driver of mortgage default. Later, using loan-level credit bureau data, Elul et al. (2010) show that negative equity and liquidity problem have comparably sized marginal effect on mortgage default. Besides, the impact of liquidity constraints on mortgage default also increases for higher combined loan-to-value ratio.

Meanwhile, it has also shown that house declines, or the subsequent negative equity itself, does not guarantee home mortgage default. Using the non-prime mortgage data from Arizona, California, Florida, and Nevada, Bhutta, Dokko and Shan (2010) find that, after controlling for job losses or other income shocks, even when the house equity falls to -62 percent of the house value, only half of the borrowers will choose to default. Similarly, using the data from the Massachusetts between 1989 and 2007, Foote, Gerardi and Willen (2008) find that for households with negative equity in 1991:Q4, only about 6.4 percent of them is foreclosed in the subsequent three years. The same with the idea in Gerardi, Shapiro and Willen (2007), Foote, Gerardi and Willen (2008) state that negative equity of the houses is the necessary condition for home mortgage default, not sufficient condition. For houses with negative equity but the households have enough money for loan payment, they can wait for house price increase. Moreover, for households with liquidation problems but with positive equity, they can just sell the house, repay the loan and get the proceeds. However, for households with both liquidation problems and negative equity, selling the houses themselves is no longer necessarily the best choice for those households. In this case, foreclosure is more likely to happen as it can reduce the losses of households with negative equity to some extent.

Some other papers focus on other relevant factors on the relationship between house prices and mortgage default. Similarly, using the probit model, Gent and Kudlyak (2011) put attention on the impact of state recourse laws on mortgage default based on loan-level data. According to their results, home mortgage borrowers are less likely to default in recourse state at the same probability of negative equity, as the recourse laws low the sensitivity of mortgage borrowers to negativity equity. More importantly, in recourse states, borrowers are more likely to use lender-friendly, such as short sales and deed-in-lieu, to dispose the mortgage default. The authors argue that the mortgage default disposition pattern results from the higher bargaining power of mortgage lenders given by the recourse laws. Similarly, Ambrose, Buttimer and Capone (1997) also find that lenders recourse on other assets of borrowers besides the houses lowers the mortgage default probability. However, Gusio, Sapienza and Zingales (2013) argue that state laws in respect of recourse have no effect on mortgage default, due to borrowers' lack of knowledge on relevant laws, and the fact that the houses are the only available asset for most borrowers.

Similarly, Mian, Sufi and Trebbi (2015) examine the influence of state judicial laws on mortgage default. Based on the loan-level data from US, they find that in non-judicial state mortgage default is twice likely to be disposed by foreclosure between 2007 and 2009. Besides, by using judicial laws as an instrument for foreclosure, they examine the impact of foreclosure on house prices and estimate that foreclosures contribute 33 percent of the house price declines. The authors argue that the foreclosure spillover effect on house price is entirely through the supply channel in house markets. Meanwhile, Ambrose, Buttimer and Capone (1997), argue that longer time span between mortgage default and foreclosure, more corresponding to the case in judicial states, increases the mortgage default probability.

Only few studies focus on the interaction of mortgage default and house prices. Based on the state-level data from US, Calomiris, Longhofer and Miles (2013) use Panel VAR model and relevant functions to examine the interaction of foreclosure on house prices, and the opposite impact from house price on foreclosure. Their results suggest that foreclosure and house price are negatively relative with each other. More specifically, the impact of foreclosure on house price is higher than the opposite one. Instead interpreting their results using the existing supply effect or disamenity effect of foreclosure on house price, Calomiris, Longhofer and Miles (2013) state the interaction of foreclosure and house prices result from the strategic choices of homeowners and lenders.

3. Mortgage default risk indicators

In this paper, we use three different home mortgage default risk indicators, respectively the Mortgage Default Risk Index (MDRI), Homes Foreclosed (HF) and Foreclosure Re-Sales (FRS). The MDRI is a new default risk indicator developed by Chauvet, Gabriel, and Lutz (2016). It's calculated on the basis of search volume index (SVI) data, which is published by Google Trends since January, 2004, available at different frequencies. The SVI reflects the search frequency of each search term. It a normalized index on the basis of the highest search frequency of each search term. The index ranges from 0 to 100 within each sample period, where 100 represents the time point at which the search term reaches its highest search frequency. Moreover, the search frequency at other time points are normalized by the highest search frequency as a percentage of it. Chauvet, Gabriel and Lutz (2016) collect the aggregate SVI data for terms like "foreclosure help" and "government mortgage help"[2] and calculate the daily, weekly and monthly MDRI[3], based on the mind that users searching for these terms deliver their concern about mortgage default and foreclosure. The monthly MDRI reflects the default risk level in house market, using 100 as the base value of default risk at the first available date, January 2004.

The MDRI has three special features. First, compared with other default risk indicators that are based on the information from mortgage lenders, the MDRI is calculated on the basis of the information directly from mortgage borrowers, enabling the indicator to capture the information on mortgage distress from potential delinquent mortgage borrowers. Besides, this also make sure the MDRI cover the interaction of two mortgage default triggers, negative equity and loss of income, as households will take both triggers into account when considering their mortgage condition. Second, as the MDRI is based on real-time Google search query data, it is less affected by information lag, which is common in other default risk indicators. Last, instead of using questionnaires and asking the mortgages borrowers to answer sensitive questions regarding their default risk, which affects the reliability of the data collected, the MDRI is calculated on Google search query data and more useful to reflect

[2] For monthly MDRI calculation, Chauvet, Gabriel and Lutz (2016) use "foreclosure assistance+foreclosure help+government assistance mortgage+home mortgage assistance+home mortgage help+housing assistance+mortgage assistance program+mortgage assistance+mortgage foreclosure help+mortgage foreclosure+mortgage help" as the search term to obtain the joint SVI.

[3] Actually, it's not reported how the monthly MDRI is constructed in the paper of Chauvet, Gabriel and Lutz (2016). However, they do report the construction method of daily MDRI, so we can analogize the construction of monthly MDRI. They calculate the log first-difference value of the SVI data at the first available date and those at other time points. Through the calculation, the SVI data at the first available date, January 2004, is set to be the base value. Thus, the level MDRI measures the change of SVI relative to the first available value at January 2004.

sensitive information. The MDRI provides a more reliable measure of the overall mortgage default risk in the house market.

In their paper, Chauvet, Gabriel and Lutz (2016) have examined the predictive power of daily, weekly and monthly MDRI on other housing variables and the relationship between them. Specifically, for monthly MDRI data, the authors have assessed the relationship between the MDRI and other housing and financial variables, including housing sentiment from the University of Michigan Consumer Sentiment Survey, housing returns calculated from Case-Shiller and FHFA, delinquencies and foreclosure indicators. Their results suggest that the monthly MDRI does have predictive power on these variables. To be more specific, the monthly MDRI is shown to be the Granger cause of housing returns calculated based on Case-Shiller or FHFA house price indices. Besides, the increase of the MDRI will lead to drop in housing returns. However, in their paper, Chauvet, Gabriel and Lutz (2016) only examine the relationship between MDRI and the house returns for the entire house market. In comparison, we use two house value indices, bottom tier and top tier house value indices, to separate the house market into two different parts. This gives us the chance to examine the impact of default risks on different kinds of house markets and to further study the channel from default risk to house prices.

The HF and FRS are another two default risk indicators used in our research. The HF is the number of homes (per 10,000 homes) that were foreclosed upon in a given month. A foreclosure occurs when a homeowner loses their home to their lending institution or it is sold to a third party at an auction. The FRS provides the percentage of home sales in a given month in which the home was foreclosed upon within the previous year (e.g. sales of bank-owned homes after the bank took possession of a home following a foreclosure). Both the HF and the FRS are the default risk indicators provided by Zillow, available at the metro-level from Zillow's website.[4] Different from the MDRI, the HF and FRS only measures the default risk of home mortgages to be in default and finally end up with foreclosure. Considering the MDRI is an aggregate amount variable but the HF and FRS are relative amount variables, we use the first difference value of the MDRI, and use the original value of the HF and FRS in our estimations.

There are three different ways for home mortgage lenders and borrowers to deal with mortgages already in default but won't be cured, respectively short sale, deed in lieu, or foreclosure. Moreover, in the foreclosure procedure, the house will be listed at a property auction. If the house is sold at the auction, the foreclosure procedure ends; if not, the house become bank-owned property. Compared with the HF and FRS, the MDRI provides an overall reflection of the default risk condition in the home mortgage market, covering all the three scenarios. However, the HF can only measure the risk of mortgages to be in default and end up in the form of foreclosure, either sold in the auction or become bank-owned property. The FRS is the most restricted default risk indicator, only covering the risk of mortgages in default to be bank-owned property through foreclosure procedure. In other words, the HF and FRS can only reflect the risk of mortgages to be in foreclosure, while the MDRI can also cover the risk of mortgages ending up in other default ways.

[4] Zillow HF and FRS data is available at https://www.zillow.com/research/data/.

4. Methodology

With the introduction of Vector Autoregressive model in panel data settings (Holtz-Eakin, Newey and Rosen, 1988), in this paper, the Panel Vector Autoregressive (PVAR) model is employed to quantify the dynamic impact of default risk on house value. Similar with the VAR model, all variables in PVAR model are treated to be endogenous and interdependent, but a cross sectional dimension is added to PVAR's representation. Each variable in the system is regressed on its own lags and the lagged value of the other variables. In some cases, control variables are also included into the PVAR equation as exogenous variable. A general equation of PVAR model for metropolitan statistical area *i* is as follows:

$$\begin{aligned} &y_{i,t} = A_0 a_{i,t} + A_1 y_{i,t-1} + \ldots + A_p y_{i,t-p} + u_{i,t} \\ &(i = 1, \ldots, N; t = 1, \ldots, Z) \end{aligned} \qquad (1)$$

where $y_{i,t}$ denotes a vector of $k \times 1$ dependent variables for metropolitan statistical area *i* (*i* = 1, ..., N) at time *t* (*t* = 1, …, T) ; A_1 to A_p is respectively the $k \times 1$ coefficient matrix for each lag *p* = 1, …, P; $a_{i,t}$ is a vector of deterministic terms (linear trend, dummy or a constant) with a coefficient matrix of A_0, and $u_{i,t}$ denotes a vector of reduced form errors, which has zero mean and a metro-specific variance.

In some literature, the fixed effect term is included into the PVAR equation to control for the unobserved time-invariant idiosyncratic characteristics that is specific to metropolitan statistical area i. However, the fixed effect estimator would be biased with the existence of lagged endogenous variable. In contrast, following Love and Zicchino (2006), we use Helmert transformation to overcome the problem of fixed effect, which preserves homoscedasticity and would not cause serial correlation. All the data are forward de-meaned using Helmert-transformation before being used in estimations. And the generalized method of moments (GMM) is employed to estimate the coefficients in the PVAR system.

After establishing the PVAR model, we use impulse response function and forecast error variance decomposition function to quantify the effect of default risk on house value. Following the existing PVAR literature, we employ the Cholesky decomposition when conducting impulse response analysis, which models the residuals matrix as a recursive, triangular system. In this case, the ordering of endogenous variables in the model is of importance for the impulse response results. As mentioned in previous sections that negative equity is an essential reason for default, the default risk would react to the change of house value with no lags. Besides, there would be a gap between the occurrence of mortgage default and the dispose of the houses used as collateral, either foreclosed by the mortgages lenders or sold by the borrowers. Hence, the house value will react to changes of default risk with some lags. Therefore, in our selected ordering of variables for the PVAR model, the house value variables are put at the first position, followed by the default risk variables. Here, we primarily assume that the house value respond contemporaneously to default risk shocks, whereas the latter only responds to the former with a lag. Nonetheless, our main results are robust to different variable orderings, either the house value variable or the default risk variable at the first position. The 95% confidence intervals of the impulse responses are generated in Monte Carlo simulations. Forecast error variance decomposition is another method to examine the predictive effect of the variables within the PVAR framework, which quantifies the contributions of one endogenous variable on the other endogenous variables within the PVAR model.

5. Data

The main regression variables used in our research include three default risk measuring variables and two indices of house value. The three indicators are respectively the Mortgage Default Risk Index (MDRI), Homes Foreclosed (HF) and Foreclosure Re_Sales (FRS). As the city-level MDRI data is only available for 20 cities, we use the state-level MDRI data as the substitution of metropolitan-level data for all the metropolitans in each state in our research, which is available for 44 states. The MDRI data is obtained online.[5] The HF and FRS is another two default risk indicators used in our research, both provided by Zillow and available at the metro-level from Zillow's website.[6] Different from the MDRI, the HF and FRS only measures the default risk of home mortgages to be in default and finally end up with foreclosure. Considering the MDRI is an aggregate amount variable but the HF and FRS are relative amount variables, we use the first difference value of the MDRI, and use the original value of the HF and FRS in our estimations.

In respective of the house value indices, we use bottom tier (BT) and top tier (TT) house value indices in our regressions. Specifically, the bottom tier house value indices are the median estimated home value for all bottom-tier homes within a given region. Bottom-tier homes are the homes that fall into the bottom third of home value within a given region. The top tier house value indices are the median estimated home value for all top-tier homes within a given region. Top-tier homes are homes that fall into the top third of home value within a given region. The same as the HF and FRS, both the two groups of house value indices are

[5] The monthly state-level MDRI data is available at https://github.com/ChandlerLutz/MDRI_Data.
[6] Zillow HF and FRS data is available at https://www.zillow.com/research/data/.

published by Zillow. In our research, we use metro-level house value indices data and obtain the data from Zillow's website.[7] The log first difference value of house value indices is used in our regressions.

Further, we include some control variables into our model to eliminate the impact of other factors relevant to the change of house prices but not in our interest. These variables include total nonfarm employees (Emp), new private housing units authorized by building permits (Perm), industrial production index (Indpro), producer price index for all commodities (Ppiaco), University of Michigan consumer sentiment (Umcsent), effective federal funds rate (Fedfunds) and S&P 500 Index (SP500). To be more specific, Emp and Perm are state-level data obtained respectively by Census Bureau of U.S. and Bureau of Labor Statistics of U.S., and we get the data from Datastream. Just like the case of MDRI, we use state-level data as the substitution of metro-level data for all the metropolitans in each state due to metro-level data availability. Meanwhile, we obtain the country-level data of Indpro, Ppiaco, Umcsent and Fedfunds and SP500 from the Federal Reserve Bank of St. Louis Economic Data and use the data as metro-level substitution for all the metropolitans. The log first difference value of all the control variables are used in our regressions, with the only exception of Fedfunds, for which the original value is used in our regressions.

[Table 1]

All the data used in our research is at the monthly level, ranging from 2004 January to 2017 February. The final dataset covers 92 metropolitans in 25 states of the U.S. This is mainly determined by the availability of the HF and FRS data. And we have excluded some

[7] Zillow house value indices are available at: https://www.zillow.com/research/data/.

metropolitans as there are too many missing value in their time series. Table 1 tabulates the descriptive statistics of all endogenous variables used in our estimations.

The monthly mean value of the two indices of house value and the three different default risk variables are plotted in Figure 1. As shown in the top two panels of the figure, the bottom tier and top tier house value indices experience increases and reach their peak at around July 2006, corresponding to the period of housing market boom. But after that both the house value indices keep going down until 2012 and restores to the level at the beginning of 2004. And then the house value indices enter another increasing panel. The third panel plots of the monthly mean value of the MDRI. It's shown that the value of MDRI keep stable at around 100 before 2006. It then begins to rise and accelerates in 2007 and 2008, and finally peak at more than 250 at around January 2009, 2.5 times higher than the value before 2006. After that, the MDRI keeps dropping in the subsequent years and gets back to the level before 2006 at around January 2013. The bottom two panel shows the plot of the monthly mean value of the HF and FRS. Similar to that of the MDRI, the mean value of the HF and FRS keep at a low level, smaller than 5, before 2007. Then, the two indicators experience a quick increase in 2007 and 2008. After fluctuating at a high level in the next two years, the value of the two indicators keep dropping till 2013, and then begin to fluctuate at a relatively low level again.

[Figure 1]

Overall, the value of default risk indicators are closely related to that of house value indices. Specifically, the increasing periods of house value indices are mostly corresponding to the periods in which the MDRI, HF and FRS are relatively low, while the decreasing period of house value indices is corresponding to the period in which the value of the MDRI, HF and FRS are relatively higher. This is in line with previous findings that mortgage default risk is negatively related with house prices.

6. Results

This section presents the empirical results. We first present the results from general analysis, and shift to grouped analysis afterward.

6.1 General analysis

We use panel vector autoregressive (PVAR) model to examine the predictive effects of default risk (respectively measured by the MDRI, HF and FRS in three PVAR specifications) on house value. Based on the PVAR framework, we conduct impulse response analysis and forecast error variance decomposition to quantify and compare the economic magnitude of default risk's effect on bottom tier and top tier house value. The lag length employed in the PVAR model is 4, chosen according to the Bayesian information criterion (BIC).

Based on the PVAR model established, we first conduct Granger causal relationship test to examine the predictive effect of default risk on house value indices. The test results are shown in Table 2. Column *PVAR1*, Column *PVAR2*, and Column *PVAR3* respectively present the test results for the PVAR models in which the default risk is measured by the MDRI, HF and FRS. In line with the findings of Calomiris, Longhofer and Miles (2013) and Garardi et al. (2015), we find that default risk is the Granger cause of house value, no matter what the default risk measuring variables used in the PVAR models. Specifically, the results in Table 2 show that the null hypothesis that excluded variable (default risk) does not Granger the equation variable (bottom tier or top tier house value) is rejected in all cases at the 1% significance level.

[Table 2]

After examining the Granger causal relationship from default risk to house value indices, we conduct impulse response analysis to measure the economic magnitude of the effect of default risk on house value indices. The impulse response results are shown in Figure 2 represented by black solid line, and the shaded areas give the 95% confidence interval of the estimated impulse responses. It shows that the solid lines are always below the 0 line, regardless of the default risk measuring variables used in the PVAR model, which reflects that mortgage default risk has a negative effect on house value indices. Thus, an increase in default risk will lead to drops in house value indices. And the responses of house value are most significant at about 3 to 4 periods after the innovation of default risk. More importantly, the 0 line is not included into the 95% confidence interval in most periods, and thus these responses are significantly different from 0. This supports our finding that mortgage default risk is the Granger cause of house value indices within the PVAR framework, which is also in line with previous findings in other literature.

[Figure 2]

The impulse response results provide us with some primary evidence about the differences between default risk's effects on bottom tier and top tier house value indices. One potential problem is that the results only reflect the absolute effect of default risk on house value, which neglects the influence of the size of house value' standard deviation in the

PVAR regressions. Following Calomiris, Longhofer and Miles (2013) and Ahlfeldt, Moeller, and Wendland (2015), we solve this problem by standardizing the impulse response results, more specifically, by dividing the responses shown in Figure 2 by the standard deviation of the corresponding response variables.

The standard impulse response results are shown in Figure 3. The yellow solid lines in each panel plot the standard impulse responses of top tier house value indices to default risk shock, while the grey dash line represent he standard impulse responses of bottom tier house value indices. As the effect of default risk on house value indices are negative, a lower line means the effects of default risk on the corresponding house value indices are higher. Specifically, in Panel A, in which the default risk is represented by the MDRI, the yellow solid line is significantly lower than the grey dash line in the first 9 periods after the innovation of default risk. The yellow solid line surpasses the later one in subsequent periods, but only with slight difference. This reflects that the effect of default risk on top tier house value indices is higher when it is measured by the MDRI. In comparison, in Panel B and Panel C, in which the default risk is respectively represented by the HF and FRS, the yellow solid lines are above the grey dash lines as a whole. This suggests that the effect of default risk, measured by HF and FRS, is lower on top tier house value indices.

[Figure 3]

After doing the impulse response analysis, we conduct forecast error variance decomposition analysis to quantify and compare the contributions of default risk on bottom tier and top tier house value indices. Here, we concentrate on the forecast error variance decomposition results for the 6th, 12th, 18th and 24th period after giving a one-standard-deviation on default risk in period 0. The results are tabulated in Table 3.

According to the results in Table 3, in the case using the MDRI to measure default risk, the contribution of default risk on the top tier house value indices is relatively higher than that on the bottom tier house value indices. Specifically, the MDRI can explain 0.57% of the 24-lag forecast variance of the top tier house value, while only 0.33% of the 24-lag forecast variance of bottom tier house value can be explained by the MDRI. But in the cases using the HF and FRS to measure default risk, the contributions of default risk on the top tier house value indices are shown to be higher in most lags. In the case using the HF to measure default risk, 12.23% (6.3%) of the 24-lag forecast variance of the bottom tier (top tier) house value indices can be explained by the default risk. Meanwhile, in the case using the FRS, 7.73% (3.25%) of the 24-lag forecast variance of the bottom tier (top tier) house value indices can be explained by the default risk. Overall, the contribution of default risk is shown to be relatively higher on the top tier house value when the default risk is measured by the MDRI, while the contribution is higher on bottom tier house value if we use the HF and FRS to measure default risk. This provides further evidence supporting the view that potential default risk has a higher impact on top tier house value, whereas the impact of actual default risk is higher on bottom tier house value.

[Table 3]

Overall, the impulse response results and forecast error variance decomposition results for non-grouped data both suggest that the default risk measured by the MDRI has a higher impact on top tier house value, and the default risk measured by the HF and FRS has a higher impact on bottom tier house value. Considering that actual default risk is covered by the MDRI, HF and FRS, whereas the potential default risk is only covered by the MDRI, we can get two conclusions from the above difference. First, the potential default risk does have an influence on house value. Second, unlike actual default risk which has a higher influence on bottom tier house value, potential default risk has a higher influence on top tier house value.

Previous literature has documented two possible mechanisms of default risk's impact on house value. The first channel is through the listing of foreclosed houses of delinquent borrowers, which increases the supply of houses in the market without corresponding demand increase (Anenberg and Kung, 2014; Molloy and Shan, 2013). This channel only works in the cases that the mortgage borrowers are already in default, corresponding to the default risk measured by the HF and FRS. The second channel is through a lack of house maintenance as delinquent home mortgage borrowers or mortgage lenders won't have a strong incentive to invest in property maintenance (Ghent and Kudlyak, 2011). This channel could also be in effect in the cases that the mortgage borrowers are potentially to be in default as they don't have enough money to invest in house maintenance, but it cannot completely explain the higher impact of default risk on top tier house value indices when the default risk is measured by the MDRI.

There could be another channel from the potential default risk to house value. Foote et al. (2008) state that a substantial loss of income and negative equity of the mortgage property of the borrowers are both essential causes of mortgages default. Chauvet, Gabriel and Lutz

(2016) document that a borrower with an income loss but positive equity could avoid default by selling the property and repay their mortgages. However, due to the fact that mortgage lenders tend to sell foreclosed houses urgently even at low prices (Campbell, Giglio and Pathak, 2011), potential delinquent borrowers with negative equity might also prefer to sell their houses in their own initiatives and repay their mortgages to minimize their losses. Such selling activities will increase the supply of houses in the market, just like the foreclosure sales. The excess supply of houses will negatively affect the house value in the market. In this paper, we refer this selling activity as "strategic selling" of potential default mortgage borrowers, which we thinks is the channel from potential default risk to house value.

6.2 Grouped analysis

The laws in respect of foreclosure procedures (judicial or non-judicial)[8] and recourse of the home mortgage lenders (recourse or non-recourse)[9] are different across states. Ghent and Kudlyak (2011) document that borrowers are less likely to be in default in recourse states as recourse laws lower their sensitivity to negative equity. Besides, Mian, Sufi and Trebbi (2015) document that it's twice likely for home mortgage borrowers in default to be foreclosed in states without a judicial requirement for foreclosure. These findings suggest that the foreclosure and recourse laws would affect the possibility of mortgage borrowers to be in default and the possibility of delinquent borrowers to be foreclosed. Thus, these laws may affect mortgage borrowers' concern about default and foreclosure, and further, affect their choices of actions to minimize their losses, e.g. keeping repaying their mortgages, or selling

[8] The detailed category of Judicial and Non-Judicial state is available at: http://www.realtytrac.com/real-estate-guides/foreclosure-laws/. A state will be put into the Non-Judicial state group only when the comment is "Non-Judicial only" on the website.
[9] We use the definition of Recourse state and Non-Recourse state from Ghent and Kudlyak (2011).

their houses before being foreclosed, or just waiting for foreclosure. Thus, it's essential to examine the influence of these law on the relation between house value and default risk. The followings are the detailed descriptions of laws regarding foreclosure and recourse.

Judicial states: In a state with a judicial foreclosure requirement, to foreclosure the house of delinquent borrowers, the lender must provide the court with relevant document and let the court to review the foreclosure case. The foreclosure can be conducted only when the court confirms that it the lender has enough evidence to support their foreclosure actions. Meanwhile, the borrower will be informed, who can respond to the case and raise in court any legal defenses to the foreclosure. A judicial foreclosure typically takes several months or more, providing the borrower with enough time to look for another place to live. It also gives them more time to take other actions to minimize their losses, including selling their houses and repaying their mortgages before being foreclosed. Meanwhile, the foreclosure notice also increase their concern about default, which means higher MDRI value.

Non-judicial state: In a state without the judicial foreclosure requirement, the lender can foreclosure the property of delinquent borrowers without the approval from the court. The foreclosure case will be processed more quickly. Lenders use rights that they have obtained in the original mortgage document allowing sale of the property if the borrower is delinquent on the account. A lender sends a notice of default to the borrower, and the notice is typically also filed with the jurisdiction authority. If the borrower fails to pay the debt or disputes the notice, a notice of sale is subsequently filed that begins the auction process. Even though the borrowers also receive a notice of foreclosure in advance, they are left with relatively shorter time and options without the court review process.

Recourse state: When the lender forecloses the property of delinquent borrowers used as mortgage collateral, it may be the case that the total debt owed by the borrower to the lender exceed the property sale price. In a recourse state, the lender is given the right to pursue the deficiency balance from the borrower. This will make the borrowers be more concerned about their default and compare the final losses of different options they have.

Non-recourse state: In a non-recourse state, the lender can seize and sell the property used as collateral if the borrower defaults, but if the collateral sells for less than the debt, the lender cannot seek that deficiency balance from the borrower. The recovery is limited only to the value of the collateral. Consequently, borrowers will be less concerned about their default, and be less motivated to take their own actions.

Table 4 tabulates the foreclosure and recourse laws in each of the 25 states included in our dataset. Specifically, there are 9 Judicial states and 18 Recourse states. One thing should be mentioned is that all Judicial states are also Recourse states, but not vice versa. And all Non-Recourse states are also Non-Judicial states, but not vice versa.

[Table 4]

Overall, in judicial states and recourse states, borrowers would be more concerned about their risk to be delinquent and their possibilities to be foreclosed. Hence, it's more likely for them to take their own actions to minimize losses, including selling their houses on their own initiatives before being foreclosed. The higher concern about default and foreclosure will be illustrated by higher MDRI value. In opposite, in Non-Judicial states and Non-Recourse states, borrowers are more likely to be foreclosed finally, which will be reflected by higher HF and FRS value.

Figure 4 plots of the mean value of the three default risk indicators, the MDRI, HF and FRS, in different state groups. Panel A, Panel B and Panel C in Figure 4 respectively plot the mean value of the MDRI, HF and FRS. In each panel, the mean value of the default risk indicators in Judicial states, Non-Judicial states, Recourse states and Non-Recourse states are respectively represented by the red, blue, yellow and green line. According to Panel A, the overall level of the MDRI is highest in Judicial states, followed by that in Recourse states. Meanwhile, the MDRI in Non-Judicial states are lower than that in the two state groups just mentioned, but higher than that in Non-Recourse states. In comparison, between the period from 2007 to 2013, the size order of the HF's and FRS's mean value in four subgroups are exactly opposite with the one of the MDRI. To be more specific, the HF/ FRS's mean value are highest in Non-Recourse states and lowest in Judicial states, while the mean value of the HF/ FRS in Non-Judicial states and Recourse states respectively take the second and third position. This is in line with our expectation that judicial foreclosure requirement and recourse of mortgage lenders will increase the MDRI, while higher HF and FRS will appear in Non-Judicial states and Non-Recourse states. Besides, due to the fact that all Judicial states (Non-Recourse states) are also Recourse state (Non-Judicial states), it's not surprising to find that the mean value of default risk indicators are relatively closer in Judicial states (Non-Judicial states) and Recourse state (Non-Judicial states).

[Figure 4]

One concern is the mixture of the influence of judicial foreclosure requirement and recourse on default risk. To separate these influence, for the data in Non-Judicial states, we further separate the data into Recourse group and Non-Recourse group and plot the mean value. Similar process is also conducted for the data in Recourse states. The corresponding figure is shown in Appendix. And again, the results are in line with our expectation, i.e. the MDRI's mean value are higher in Judicial states, and the mean value of the HF and FRS are higher in Non-Recourse states.

After separate all the metropolitans into the corresponding state groups according to the characteristics of the state they belonging to, we conduct the PVAR estimations again for each of the state groups and also repeat the main empirical analysis process, including the Granger causal relationship test, the impulse response analysis and the forecast error variance decomposition. We employ 4 lags in the PVAR model estimations using the grouped data.

On the basis of the new PVAR estimation using grouped data, we conduct the Granger causal relationship test for all the PVAR estimations. The test results are shown in Table 5. Compared with the causal test results from PVAR estimations using non-grouped data, the robust causal relationship from default risk to house value only exist in the results using the data of Non-Judicial state group. Specifically, for the Non-Judicial state group, the null hypothesis that excluded variable (default risk, measured by the MDRI, HF or FRS) does not Granger cause the equation variable (bottom tier or top tier house value indices) is rejected in all cases at the 10% or 1% significance level. But in the test results for estimations using data from the other three groups, the null hypothesis cannot be rejected for certain default risk indicators. For example, when the default risk measuring variable is the MDRI, we cannot reject the hypothesis that the default risk is not the Granger cause of bottom tier house value indices in the estimations using data from Judicial state group and Recourse state group. In comparison, when the default risk is measured by the HF or FRS, the causal relationship from default risk to house value indices is robust in most cases. Overall, this suggest that the effect of potential default risk, measured by the MDRI, on house value is more likely to be affected by state characteristics.

[Table 5]

After examining the causal relationship from default risk to house value indices, we use impulse response function to quantify the effect of default risk on house value in different state groups. Specifically, we get the standard impulse responses of house value in the next 24 periods after giving a one-standard-deviation shock on default risk in period 0. The standard impulse responses are calculated by dividing the impulse responses by the standard deviation of the response variables, i.e. the bottom tier or the top tier house value indices. The results are shown in Figure 5, Figure 6 and Figure 7, in which the default risk is respectively measured by the MDRI, HF and FRS. Panel A, Panel B, Panel C and Panel D in each of the figure respectively plot the response results from estimations using the data of Judicial states, Non-Judicial states, Recourse states, and Non-Recourse states. The grey dash line in each of the panels reports the standard impulse responses of bottom tier house value, and the black solid line reports the responses of top tier house value indices.

[Figure 5]

[Figure 6]

[Figure 7]

According to the result in Figure 5, in which default risk is measured by the MDRI, except for the results corresponding to Non-Recourse states (Panel D), the responses of bottom tier house value to the shock from default risk is lower than that of the top tier house value across different state groups. Although for Non-Judicial states, the response of bottom tier house value is slightly higher than the response of top tier house value 9-period after the innovation on default risk, the cumulative response of the bottom tier is still lower. In comparison, in Non-Recourse states, even though the response of bottom tier house value is relatively lower than that of the top tier in the first 4 periods after the innovation on the MDRI, it overpasses the later one in subsequent periods. And the overall response of bottom tier house value is shown to be higher. As a comparison, in Figure 6 and 7, where the default risk is measured by the HF and FRS, the response of bottom tier house value is higher than that of the top tier house value. Although in some cases (Panel B and Panel D in Figure 6), the response of bottom tier house value indices is slighter lower at the first 4 to 5 periods after the innovation on default risk, it doesn't change the overall higher response of bottom tier house value.

Further, we use forecast error variance decomposition to quantify and compare the effects of different default risk variables on bottom tier and top tier house value indices across different state groups. Table 6 tabulates the variance decomposition results of house value indices at the 6th, 12th, 18th, and 24th period after giving a one-standard-deviation shock on default risk. According to the results, in the case using the MDRI to measure default risk, the overall variance decomposition results vary across state groups. Specifically, for estimations using data from Judicial states, Non-judicial states and Recourse states, the contribution of default risk is relatively lower on bottom tier house value. But for estimations using data from Non-recourse state group, the default risk has a relatively higher effect on bottom tier house value. In comparison, in the cases using the HF and FRS to measure default risk, it's shown the contribution of default risk on bottom tier house value is always higher than that on top tier house value, regardless of the state groups.

[Table 6]

In general, the impulse response and variance decomposition results from Judicial states, Non-Judicial states and Recourse states show that the default risk measured by the HF and FRS has a higher influence on bottom tier house value, while the default risk measured by the MDRI has higher influences on top tier house value. These findings are the same with that for non-grouped data. However, similar findings are not found in the results for Non-Recourse states. Considering that the states included into Non-Recourse state group have both non-recourse laws and non-judicial laws, borrowers in these states might be less likely to take their own actions, including selling their houses in their own initiatives, as these laws would reduce the concern of borrowers about their default risk. Thus, the "strategic selling" channel may not work in these states and the higher impact of the MDRI would not appear, which is proved by our results for Non-Recourse states.

7. Conclusion

In this paper, we examine how house prices of different segments of local real estate markets respond to changes in mortgage default risk. In our analysis, we focus on three measures of mortgage default risk. In addition to the percentage of home foreclosed (HF) and foreclosure resales (FRS) in local residential housing markets, we use the mortgage default risk indicator (MDRI) recently developed by Chauvet, Gabriel and Lutz (2016) which is based on the intensity of Google search queries containing keywords "mortgage" and "foreclosure" with the word "help." Chauvet, Gabriel and Lutz (2016) show that MDRI predicts housing returns and subprime credit default swap premiums. In this paper, we examine the impact of this newly developed default risk measure vis-à-vis the other two standard measures of default on the top and the bottom segments of the housing market in 92 U.S. metropolitan statistical areas. We estimate a Panel VAR model at the metropolitan area level for the period from January 2004 to February 2017. While we find that the HF and FRS measures of default are associated with price declines primarily for the bottom tier of the housing market, we establish that the MDRI index has a negative impact on primarily the top house price tier.

We extend our analysis by examining the impact of mortgage default risk on prices separately for states with judicial and non-judicial foreclosure procedure. In judicial states, mortgage lenders rely on the court system to execute the foreclosure while the non-judicial states they use out-of-court procedures (based on deeds of trust that contain power-of-sale clause) defined by state law. We find that, in both judicial and non-judicial the results we obtained for the overall sample hold: HF and FRS have a greater impact on bottom tier homes while MDRI impacts primarily the values of homes at the high end of the market.

We further analyze recourse vs. non-recourse states – a characteristic signifying whether lenders are able to pursue mortgage borrowers for the part of the debt not covered by the proceeding from the foreclosure sale. We find significant differences in the impact of default risk indices on prices. While in recourse states the MDRI index impact mostly the prices of top tier homes and the HF and FRS primarily the prices of bottom tier homes, in non-recourse states the impact of the MDRI is about the same for both tiers while the HF and FRS impact the prices of top tier homes. These findings are consistent with the “double trigger” hypothesis of mortgage default. According to this hypothesis, homeowners default on their payments not only when they face financial distress, but also when they end up with a negative equity on their home investment. The owners of relatively expensive houses not only search for information online related to the consequences of mortgage default, but also are more likely to default on their payments in states in which the mortgage loans are non-recourse.

Tables

Table 1. Descriptive statistics of all endogenous variables

Variable	N	mean	median	max	min	variance	skewness	kurtosis	p25	p75
BT	14536	146155.9	125600	648600	36900	8.24E+09	1.964	7.648	83400	172500
TT	14529	365530.3	310800	1790300	104500	4.27E+10	2.229	9.654	230400	401200
MDRI	14536	122.374	104.618	614.942	14.293	4564.038	1.429	6.520	78.716	157.084
HF	14436	6.934	4.536	106.204	0.016	69.482	3.115	18.010	1.884	8.428
FRS	14425	10.706	6.812	86.404	0.019	149.163	2.326	9.450	2.956	13.154

Note: Column Variable states the endogenous variable used in the PVAR model. Specifically, BT and TT respectively represent the bottom tier house value indices and top tier house value indices. MDRI is the mortgage default risk index. HF represents the number of homes (per 10,000 homes) that were foreclosed in a given month. FRS is the percentage of home sales in a given month in which the home was foreclosed upon within the previous year.

Table 2. The Granger causal relationship test results

	PVAR1		PVAR2		PVAR3	
Equation	**Excluded**	**F-Statistics**	**Excluded**	**F-Statistics**	**Excluded**	**F-Statistics**
BT	MDRI	16.197***	HF	25.783***	FRS	15.147***
TT	MDRI	18.116***	HF	101.282***	FRS	86.892***

*Note: The Granger causal relationship test results for different PVAR estimations are presented in the table. Column Equation shows the house value indices used in the PVAR models, which are the same in the three PVAR model settings. Specifically, BT and TT respectively represent bottom tier house value and top tier house value. Column PVAR1, Column PVAR2 and Column PVAR3 respectively present the test results for the PVAR estimations in which the default risk is measured by the MDRI, HF, and FRS. Column Excluded shows the default risk measuring variables, respectively the MDRI, HF and FRS, used in different PVAR models. Column F-statistics gives the eigenvalue for the corresponding Granger causal relationship test. The null hypothesis is that excluded variables does not Granger cause equation variables. *** represents the null hypothesis is rejected at 1% significance level.*

Table 3. The forecast error variance decomposition results for house value indices

	lag	BT	TT
MDRI	6	0.00218	0.00521
	12	0.00286	0.00557
	18	0.00320	0.00566
	24	0.00332	0.00568
HF	6	0.04541	0.03702
	12	0.08095	0.04874
	18	0.10585	0.05744
	24	0.12233	0.06361
FRS	6	0.04214	0.01762
	12	0.06565	0.02739
	18	0.07773	0.03254
	24	0.08497	0.03570

Note: The table tabulates the variance decomposition results of the row variables that can be explained by the column variables. Specifically, the results trace the variance decomposition of the house value indices at the 6th, 12th, 18th and 24th period after giving a one-standard-deviation shock on default risk in period 0. Column 1 states the variables used to measure the default risk, which is also the impulse variable. Column 2 gives the periods after the innovation on default risk. Column Bottom and Top tabulates the variance decomposition results for bottom tier and top tier house value indices.

Table 4. Foreclosure and Recourse laws across states

States	State code	Judicial/ Non-Judicial	Recourse/ Non-Recourse	States	State code	Judicial/ Non-Judicial	Recourse/ Non-Recourse
Alabama	AL	Non-Judicial	Recourse	**New York**	NY	Judicial	Recourse
Arkansas	AR	Non-Judicial	Recourse	**Ohio**	OH	Judicial	Recourse
Arizona	AZ	Non-Judicial	Non-Recourse	**Oklahoma**	OK	Non-Judicial	Recourse
California	CA	Non-Judicial	Non-Recourse	**Oregon**	OR	Non-Judicial	Non-Recourse
Colorado	CO	Non-Judicial	Recourse	**Pennsylvania**	PA	Judicial	Recourse
Connecticut	CT	Judicial	Recourse	**Rhode Island**	RI	Non-Judicial	Recourse
Massachusetts	MA	Judicial	Recourse	**South Carolina**	SC	Judicial	Recourse
Maryland	MD	Judicial	Recourse	**Tennessee**	TN	Non-Judicial	Recourse
Minnesota	MN	Non-Judicial	Non-Recourse	**Texas**	TX	Non-Judicial	Recourse
North Carolina	NC	Non-Judicial	Non-Recourse	**Virginia**	VA	Non-Judicial	Recourse
Nebraska	NE	Judicial	Recourse	**Washington**	WA	Non-Judicial	Non-Recourse
New Jersey	NJ	Judicial	Recourse	**Wisconsin**	WI	Non-Judicial	Non-Recourse
Nevada	NV	Non-Judicial	Recourse				

Note: The table presents the foreclosure and recourse laws specific to each of the 25 states included in the final dataset. Specifically, there are 9 Judicial states and 16 Non-Judicial states, and 18 Recourse states and 7 Non-Recourse states. At the metro level, within the 92 metros in 25 states, there are 30 metros belonging to Judicial states, and 62 metros belonging to Non-Judicial states. There are 49 metros belonging to Recourse states, and 43 belonging to Non-Recourse states. One thing should be mentioned is that all Judicial states are also Recourse states, but not vice versa. Likewise, all Non-Recourse states are also Non-Judicial states, but not vice versa.

Table 5. The Granger causal relationship test results for grouped data

		PVAR1		PVAR2		PVAR3	
	Equation	**Excluded**	**F-statistics**	**Excluded**	**F-statistics**	**Excluded**	**F-statistics**
Judicial States	BT	MDRI	3.42	HF	26.052***	FRS	10.52**
	TT	MDRI	18.853***	HF	35.929***	FRS	14.94***
Non-Judicial States	BT	MDRI	11.739**	HF	20.615***	FRS	20.84***
	TT	MDRI	8.796*	HF	74.992***	FRS	77.318***
Recourse States	BT	MDRI	5.09	HF	16.402***	FRS	5.46
	TT	MDRI	20.566***	HF	51.863***	FRS	42.162***
Non-Recourse States	BT	MDRI	11.65**	HF	15.152***	FRS	20.023***
	TT	MDRI	5.33	HF	52.286***	FRS	62.684***

*Note: The Granger causal relationship test results for different PVAR estimations using different data groups are presented in the table. Column State group states the data group used to estimate the PVAR model. Column PVAR1, Column PVAR2 and Column PVAR3 present the Granger test results for the PVAR estimations in which the default risk is respectively measured by the MDRI, HF, and FRS. Column Equation shows the house value indices used in the PVAR models. Specifically, BT and TT respectively represent bottom tier house values and top tier house values. Column Excluded shows the default risk measuring variables, respectively the MDRI, HF and FRS, used in different PVAR models. Column F-statistics gives the eigenvalue for the corresponding Granger causal relationship test. The null hypothesis is that excluded variables does not Granger cause equation variables. *, **, and *** respectively represent the null hypothesis is rejected at 10%, 5% and 1% significance level.*

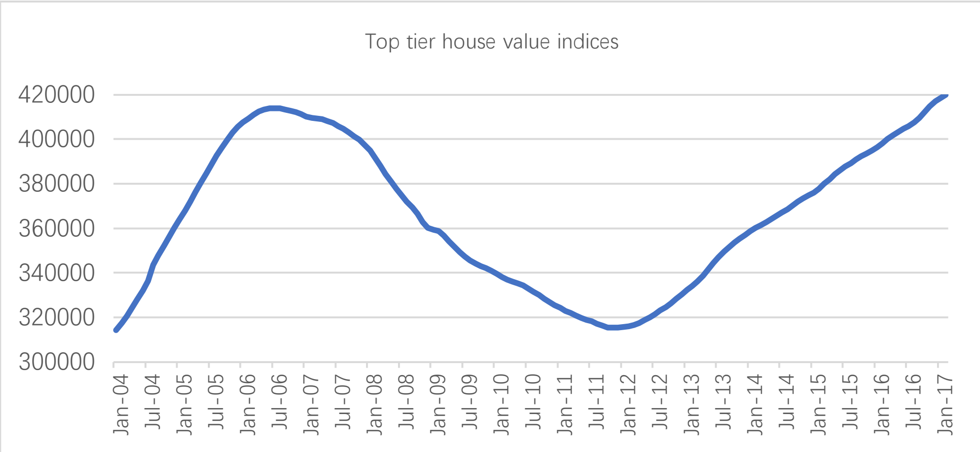
Table 6. The forecast error variance decomposition result for estimations using grouped data

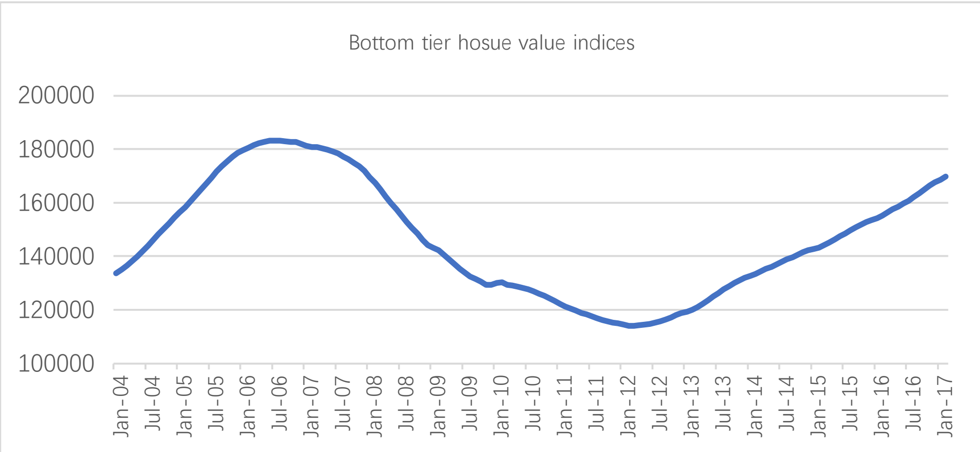
		Judicial states		Non-Judicial states		Recourse states		Non-Recourse states	
		BT	**TT**	**BT**	**TT**	**BT**	**TT**	**BT**	**TT**
MDRI	6	0.00406	0.01638	0.00142	0.00285	0.00076	0.00573	0.00568	0.00560
	12	0.00557	0.01664	0.00185	0.00314	0.00111	0.00570	0.00699	0.00658
	18	0.00600	0.01673	0.00208	0.00323	0.00130	0.00571	0.00746	0.00688
	24	0.00610	0.01674	0.00217	0.00326	0.00137	0.00569	0.00761	0.00697
HF	6	0.01783	0.00844	0.04928	0.04433	0.02608	0.01181	0.04548	0.04838
	12	0.05902	0.04061	0.08989	0.05641	0.05611	0.02054	0.08817	0.06149
	18	0.09388	0.06881	0.11731	0.06487	0.08145	0.02888	0.11708	0.07064
	24	0.11549	0.08642	0.13481	0.07066	0.10036	0.03571	0.13518	0.07674
FRS	6	0.01365	0.00334	0.05487	0.02725	0.02803	0.00683	0.06040	0.03224
	12	0.03612	0.01809	0.08804	0.04113	0.05172	0.01743	0.09974	0.05050
	18	0.05398	0.03119	0.10220	0.04639	0.06985	0.02782	0.11573	0.05720
	24	0.06465	0.03925	0.10940	0.04900	0.08226	0.03576	0.12370	0.06045

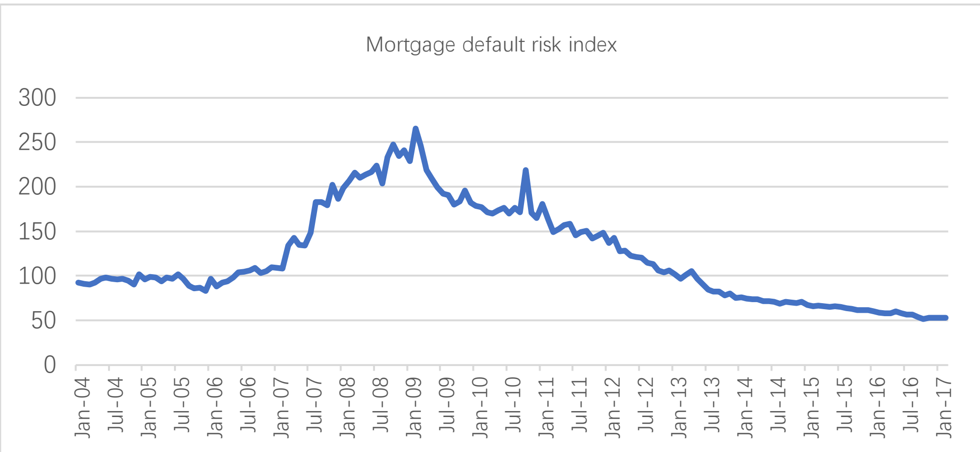
Note: The table tabulates the variance decomposition results of the row variables that can be explained by the column variables in different state groups. Specifically, the results trace the variance decomposition of the house value indices at the 6th, 12th, 18th and 24th period after giving a one-standard-deviation shock on default risk in period 0. Column 1 states the variables used to measure the default risk, which is also the impulse variable. Column 2 gives the periods after the innovation on default risk. Column Judicial states, Column Non-Judicial states, Column Recourse states and Column Non-Recourse states respectively present the variance decomposition results of the house value indices in the corresponding state groups. The sub-column BT and TT respectively tabulate the variance decomposition results for bottom tier and top tier house value indices in each state group.

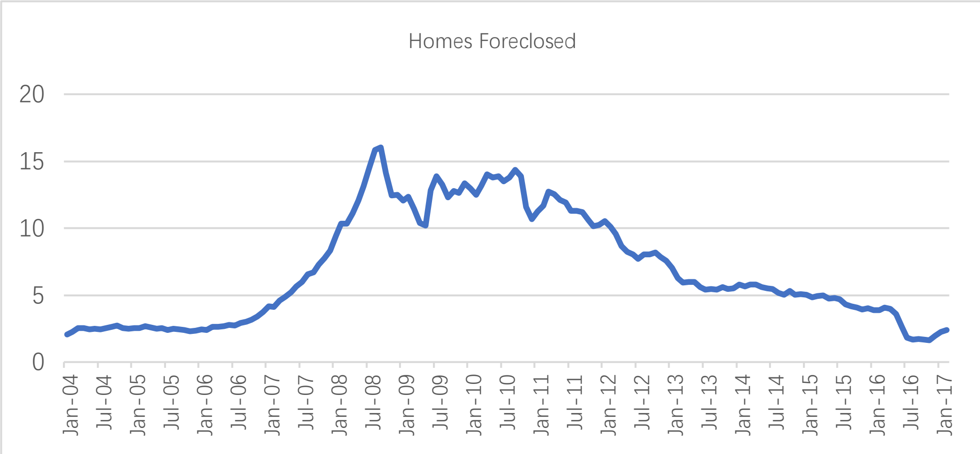
Graph

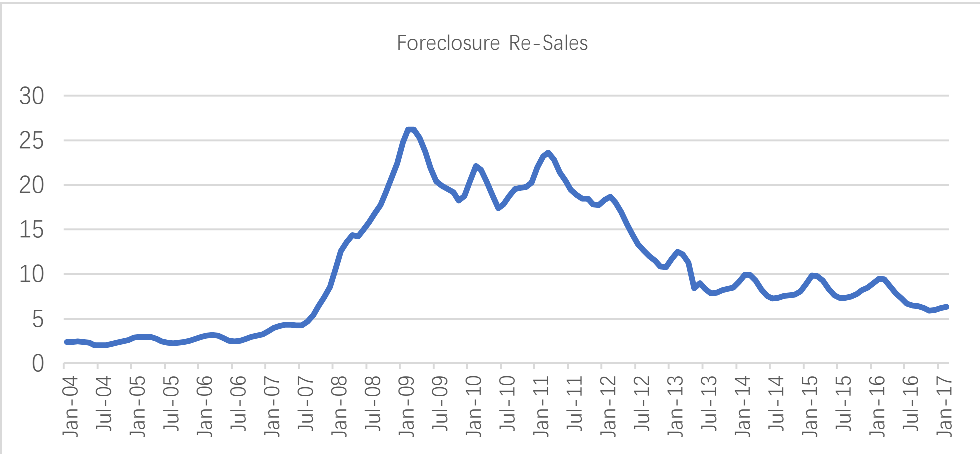
Figure 1. The mean value of house value indices and default risk indicators for non-grouped data







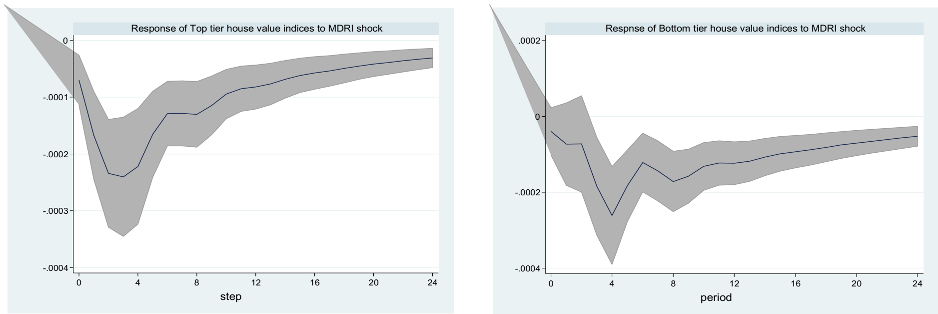




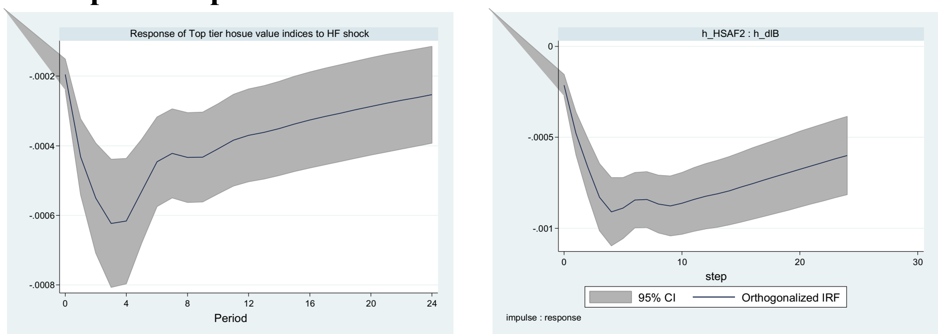
Note: This figure plots the monthly mean value of the top tier house value indices, the bottom tier house value indices, the Mortgage Default Risk Index (MDRI), Homes Foreclosed (HF), and Foreclosure Re-Sales (FRS).

Figure 2. The impulse responses of house value indices to default risk shock

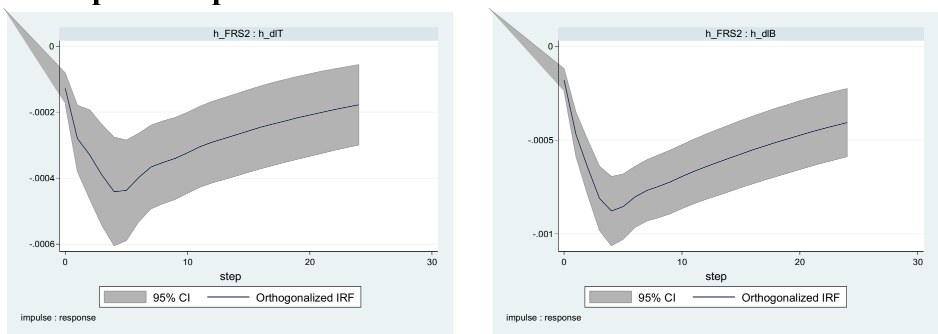
Panel A. The impulse responses of house value indices to MDRI shock



Panel B. The impulse responses of house value indices to HF shock



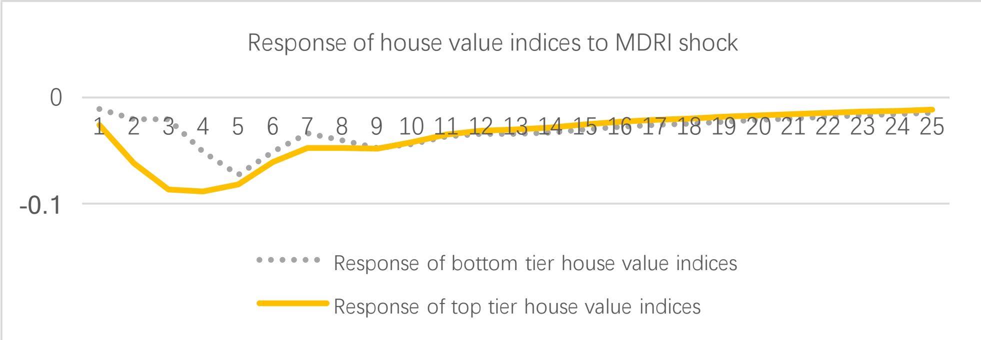
Panel C. The impulse responses of house value indices to FRS shock



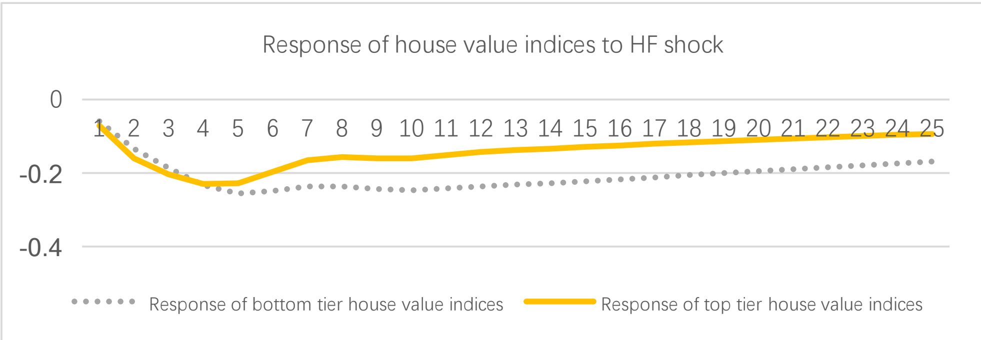
Note: The figure shows the impulse responses of house value in the next 24 periods to a one-standard-deviation shock from default risk in period 0. The three panels plot the impulse responses from PVAR estimations in which the default risk is respectively measured by the MDRI, HF and FRS. The left part of each panel plots the impulse response of bottom tier house value indices to default risk shock, while the right part plots the impulse response of the top tier house value indices. The shaded areas represent the 95% confidence intervals for the estimated impulse responses.

Figure 3. The standard impulse response of house value indices to default risk shock for non-grouped data

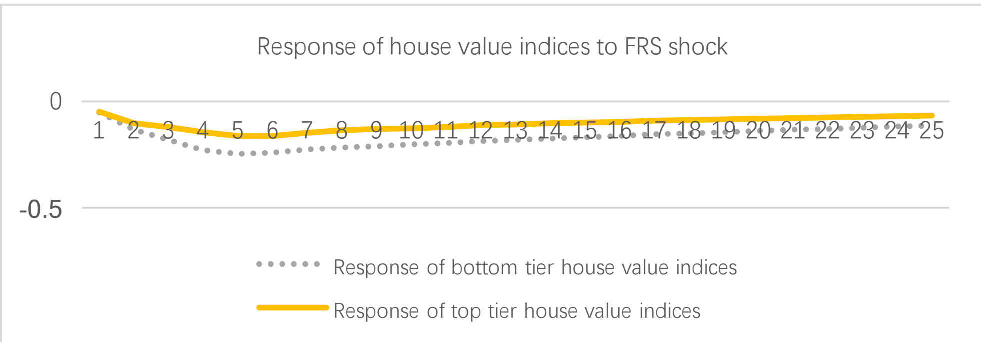
Panel A. The standard impulse response of house value to the MDRI shock



Panel B. The standard impulse response of house value to the HF shock



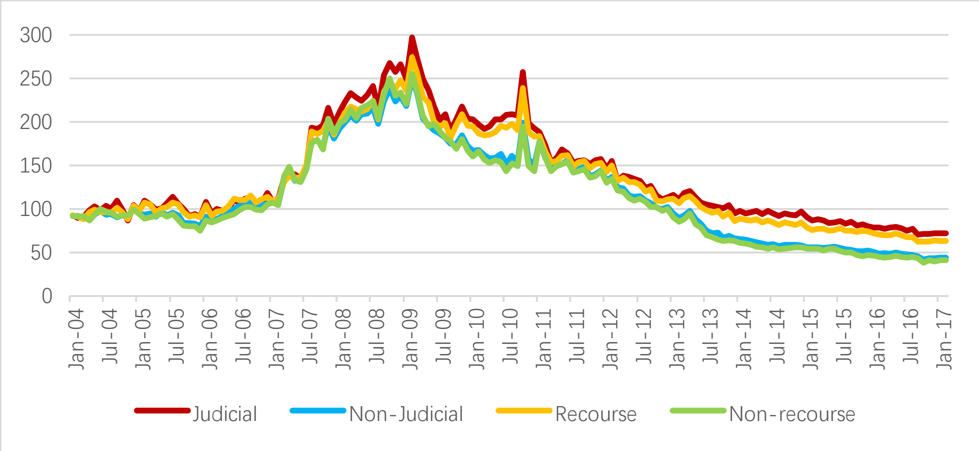
Panel C. The standard impulse response of house value to the FRS shock



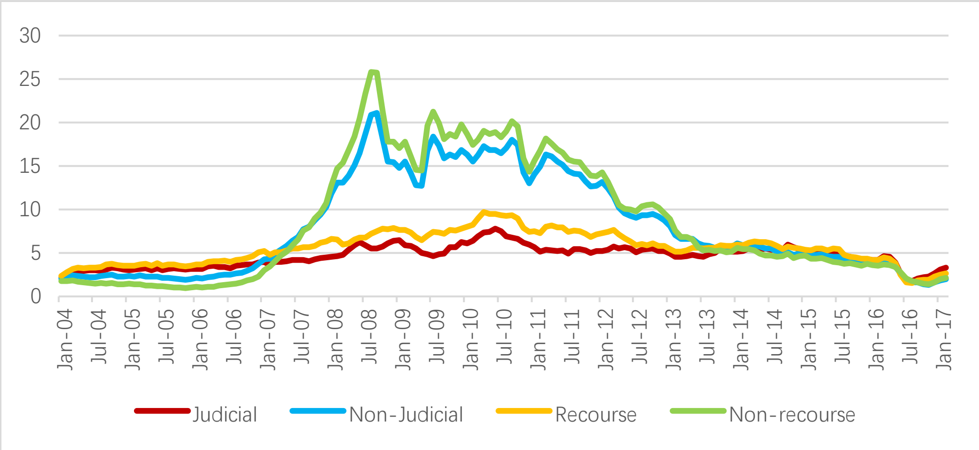
Note: The figure plots the standard impulse response of house value indices in the next 24 periods after given a one-standard-deviation shock on default risk in period 0. The three panels respectively show the standard impulse response results from PVAR models in which the default risk is measured by MDRI, HF or FRS. These standard impulse responses are calculated by dividing the corresponding impulse responses shown in Figure 2 by the sample standard deviations of the response variable. The dash line in each of the panels reports the impulse response of bottom tier house value, while the black solid line reports the impulse response of top tier house value indices.

Figure 4. The mean value of default risk indicators for different state groups

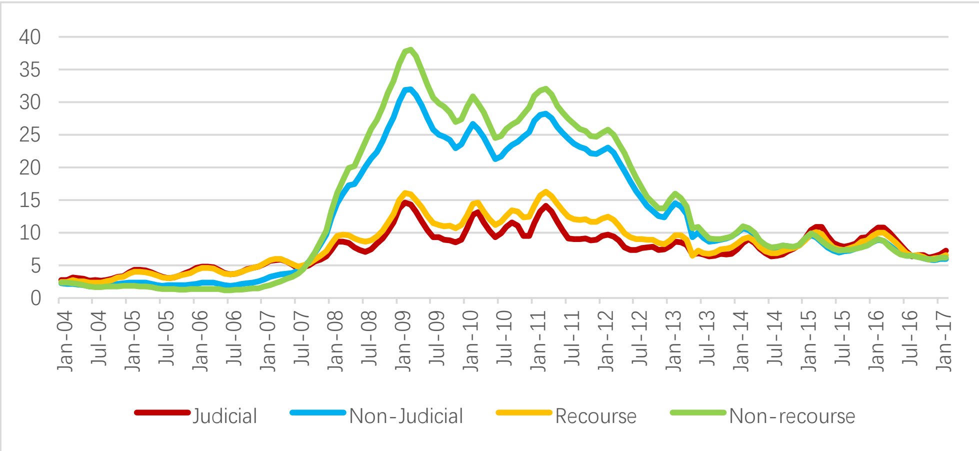
Panel A. The mean value of the MDRI



Panel B. The mean value of the HF



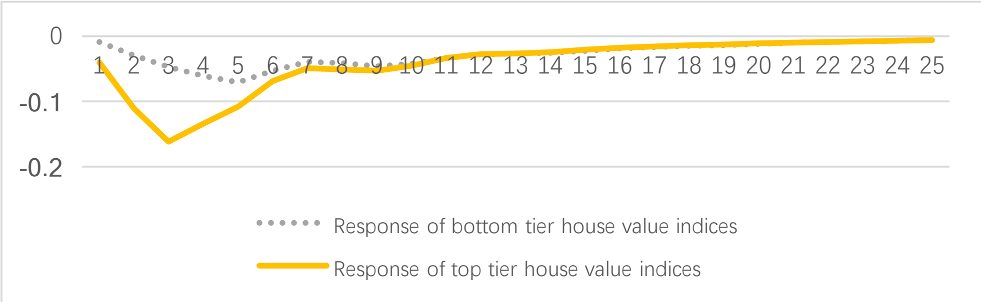
Panel C. The mean value of the FRS



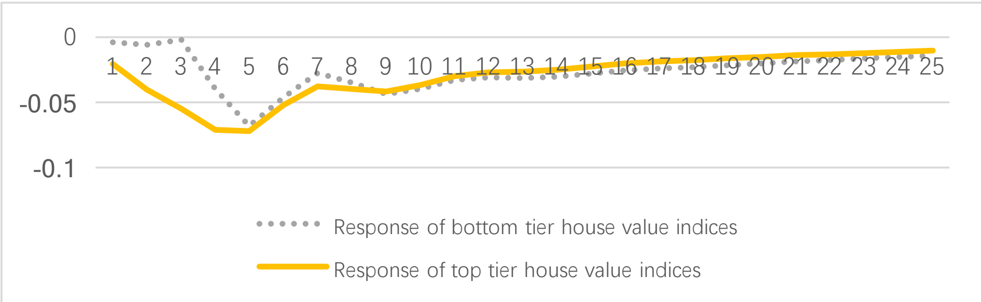
Note: This figure plots the mean value of different default risk indicators in different subgroups. Specifically, Panel A, Panel B and Panel C respectively plot the mean value of the MDRI, HF and FRS. The red line, blue line, yellow line, and green line in each panel respectively represent the mean value of the corresponding default risk indicators in Judicial state group, Non-Judicial state group, Recourse state group and Non-Recourse state group.

Figure 5. The standard impulse responses of house value to the MDRI shock

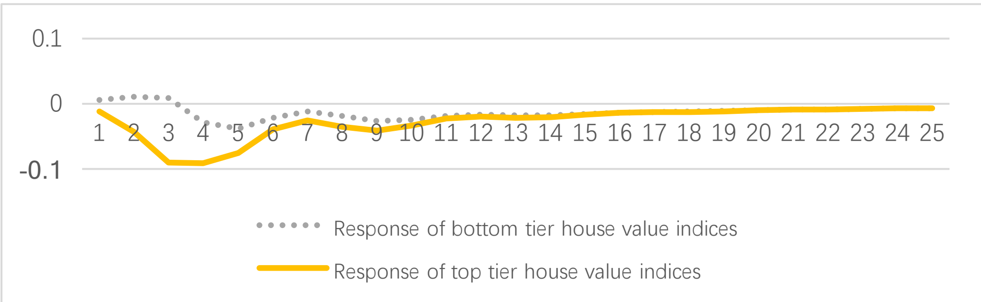
Panel A. The standard impulse responses of house value in Judicial states



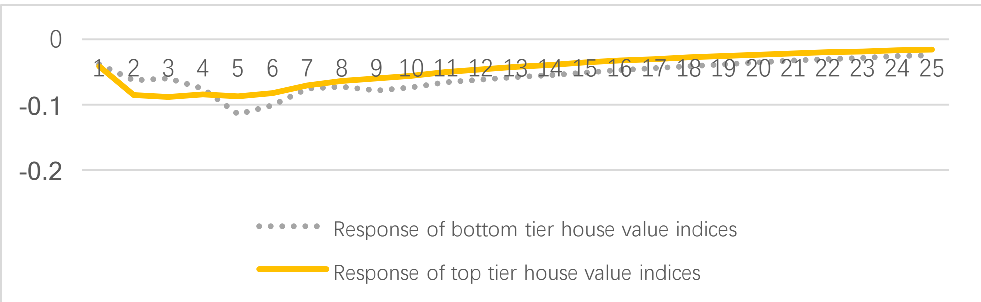
Panel B. The standard impulse responses of house value in Non-Judicial states



Panel C. The standard impulse responses of house value in Recourse states



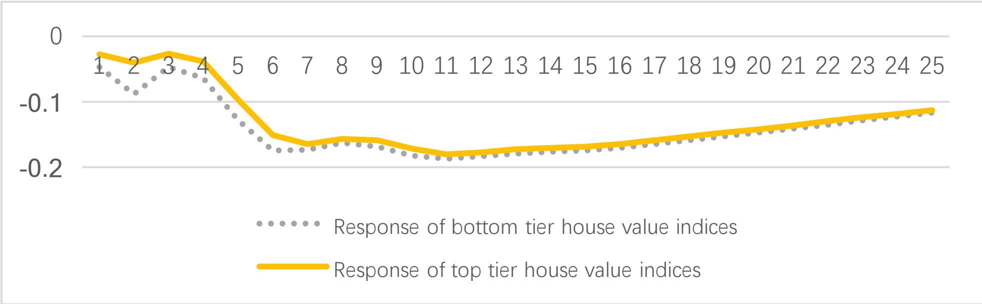
Panel D. The standard impulse responses of house value in Non-Recourse states



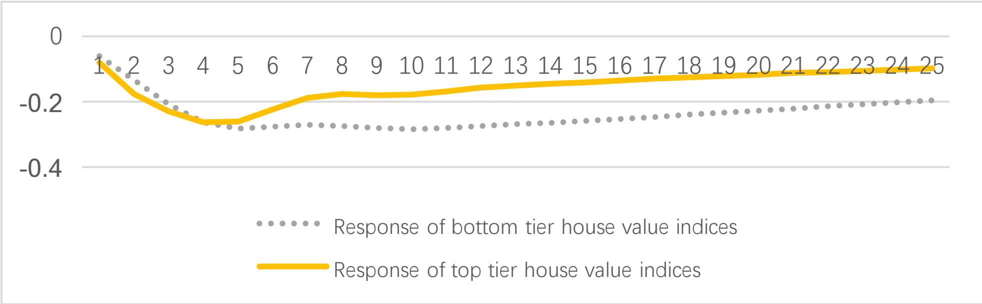
Note: The figure plot the standard impulse response of house value indices in different state groups. Panel A, Panel B, Panel C and Panel D respectively correspond to the results for Judicial state group, Non-Judicial state group, Recourse state group and Non-Recourse state group. The results trace the response of house value indices in the next 24 periods after given a one-standard-deviation shock on default risk, measured by the MDRI, in period 0. These standard impulse responses are calculated by dividing the impulse responses of house value indices by the sample standard deviations of the response variables. The dash line in each of the panels reports the impulse response of bottom tier house value, while the black solid line reports the impulse response of top tier house value indices.

Figure 6. The standard impulse responses of house value indices to HF shock

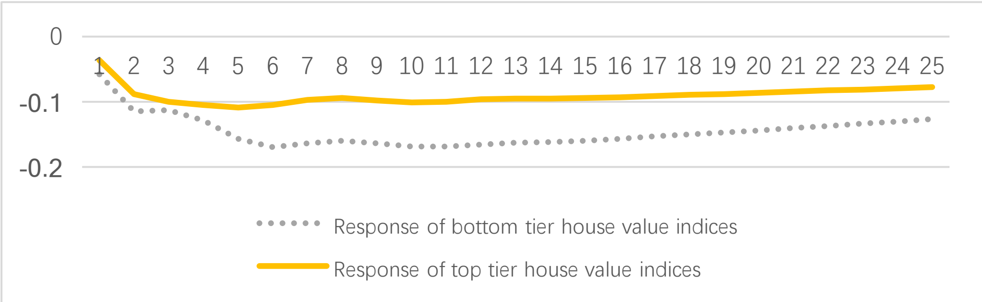
Panel A. The standard impulse responses of house value in Judicial states



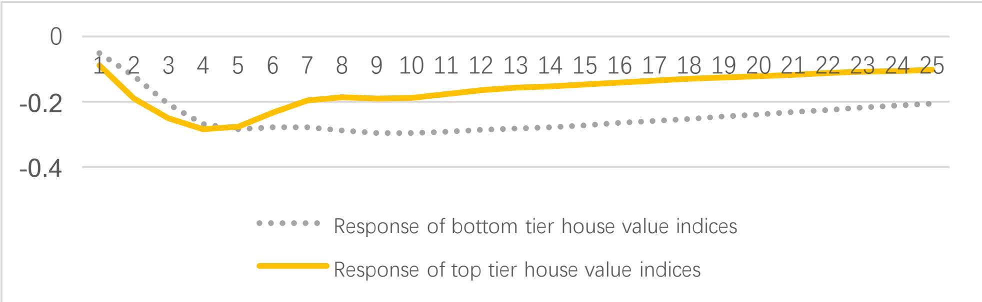
Panel B. The standard impulse responses of house value in Non-Judicial states



Panel C. The standard impulse responses of house value in Recourse states



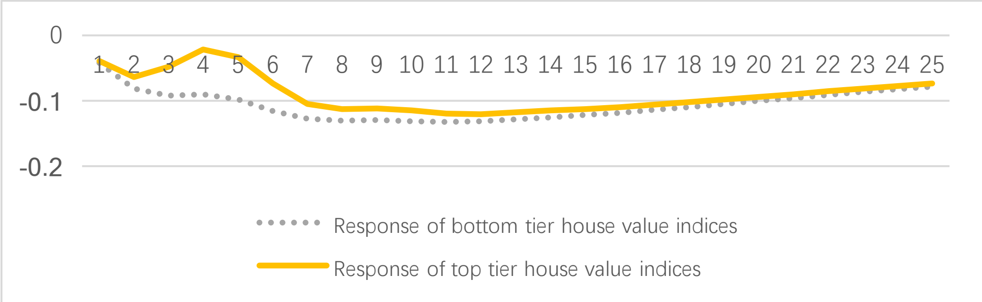
Panel D. The standard impulse responses of house value in Non-Recourse states



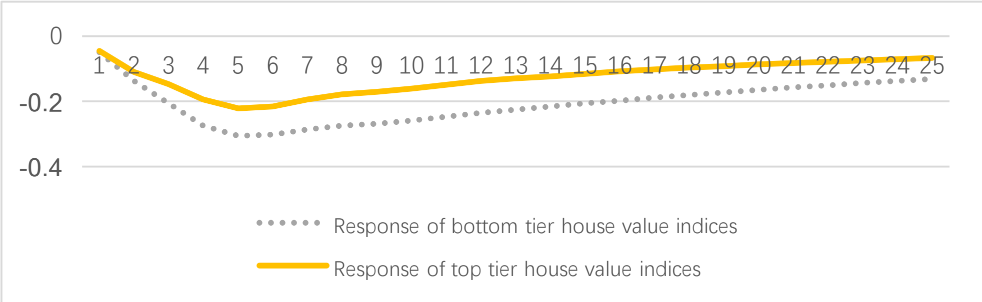
Note: The figure plot the standard impulse response of house value indices in different state groups. Panel A, Panel B, Panel C and Panel D respectively correspond to the results for Judicial state group, Non-Judicial state group, Recourse state group and Non-Recourse state group. The results trace the response of house value indices in the next 24 periods after given a one-standard-deviation shock on default risk, measured by the HF, in period 0. These standard impulse responses are calculated by dividing the impulse responses of house value indices by the sample standard deviations of the response variables. The dash line in each of the panels reports the impulse response of bottom tier house value, while the black solid line reports the impulse response of top tier house value indices.

Figure 7. The standard impulse responses of house value indices to FRS shock

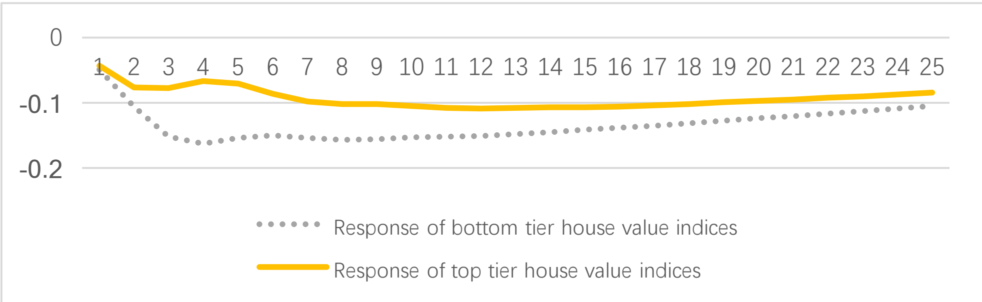
Panel A. The standard impulse response results in Judicial states



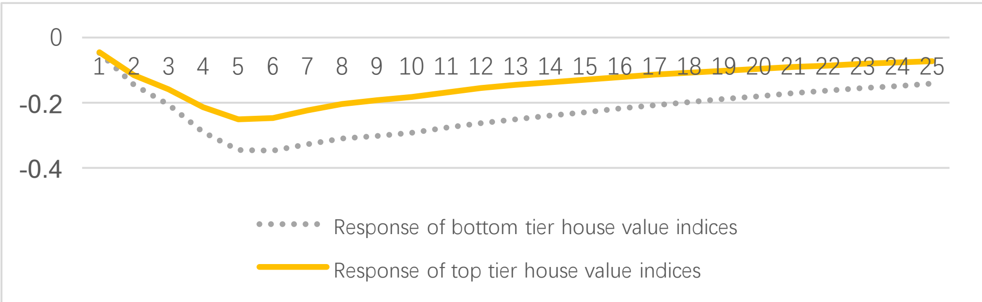
Panel B. The standard impulse response results in Non-Judicial states



Panel C. The standard impulse responses of house value indices in Recourse states



Panel D. The standard impulse responses of house value indices in Non-Recourse states



Note: The figure plot the standard impulse response of house value indices in different state groups. Panel A, Panel B, Panel C and Panel D respectively correspond to the results for Judicial state group, Non-Judicial state group, Recourse state group and Non-Recourse state group. The results trace the response of house value indices in the next 24 periods after given a one-standard-deviation shock on default risk, measured by the FRS, in period 0. These standard impulse responses are calculated by dividing the impulse responses of house value indices by the sample standard deviations of the response variables. The dash line in each of the panels reports the impulse response of bottom tier house value, while the black solid line reports the impulse response of top tier house value indices.

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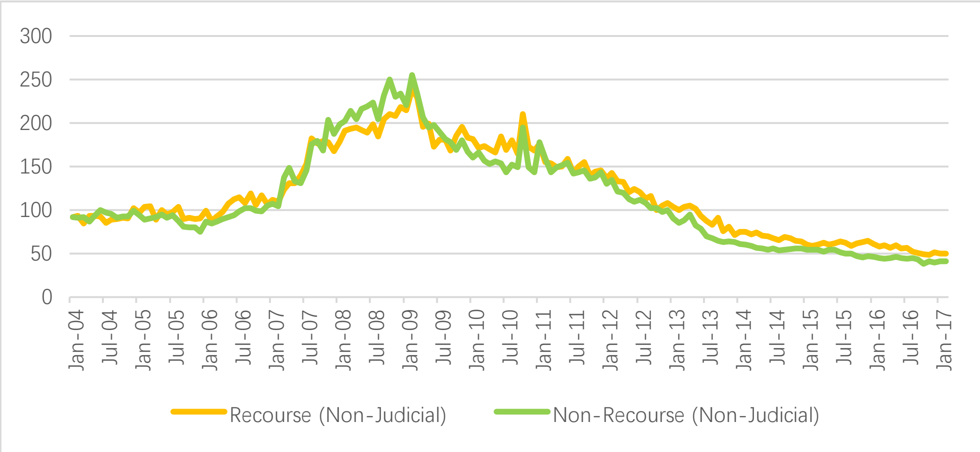
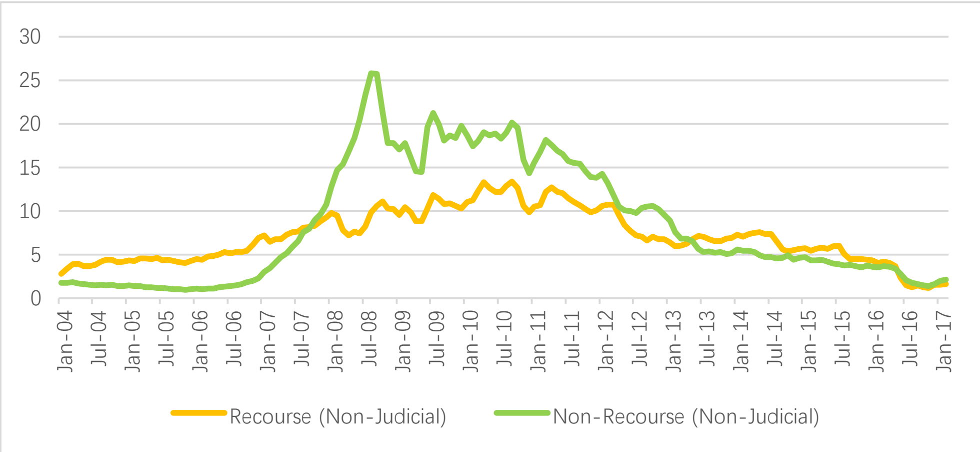
Appendix A. Mean value of default risk indicators in two subgroups

Figure 1. The mean default risk indicators in two subgroups of non-Judicial state group

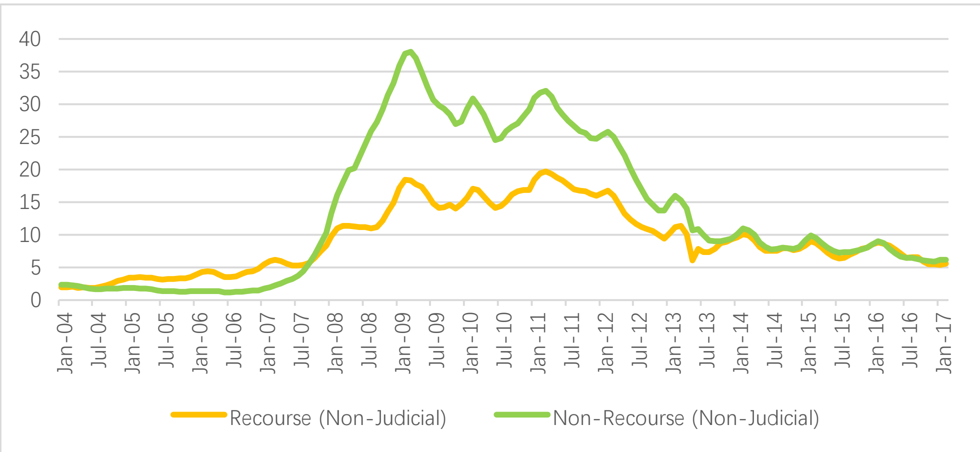
Panel A. The mean value of the MDRI



Panel B. The mean value of the HF



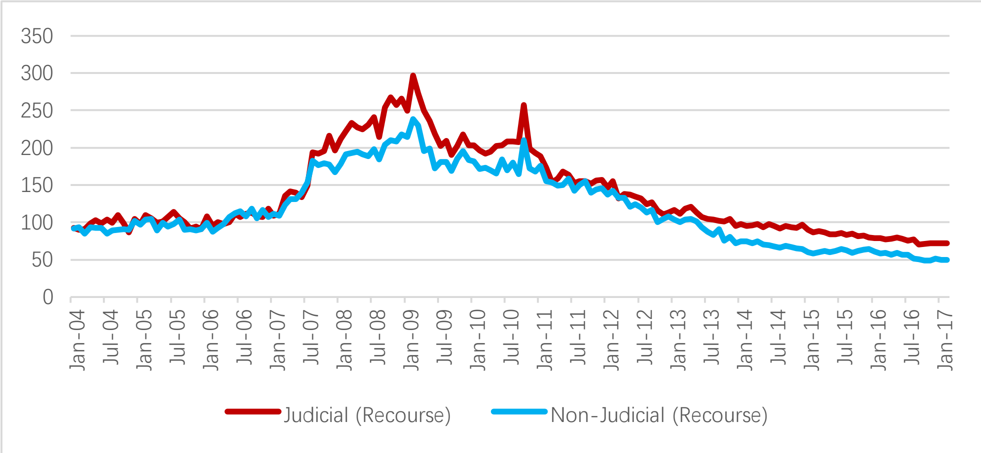
Panel C. The mean value of the FRS



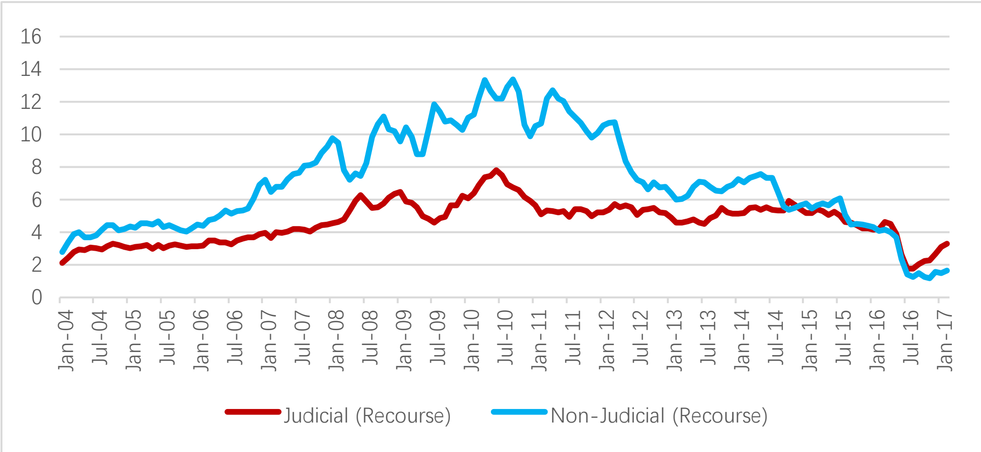
Note: This figure plots the mean value of different default risk indicators in two subgroups (Recourse and Non-Recourse state group) of the Non-Judicial state group. Panel A, Panel B and Panel C respectively plot the monthly mean value of the MDRI, HF and FRS. The yellow line and green line in each panel respectively represent the monthly mean value of the corresponding default risk indicators in Recourse (Non-Judicial) state group and Non-Recourse (Non-Judicial) state group.

Figure 2. The mean default risk indicators in two subgroups of recourse state group

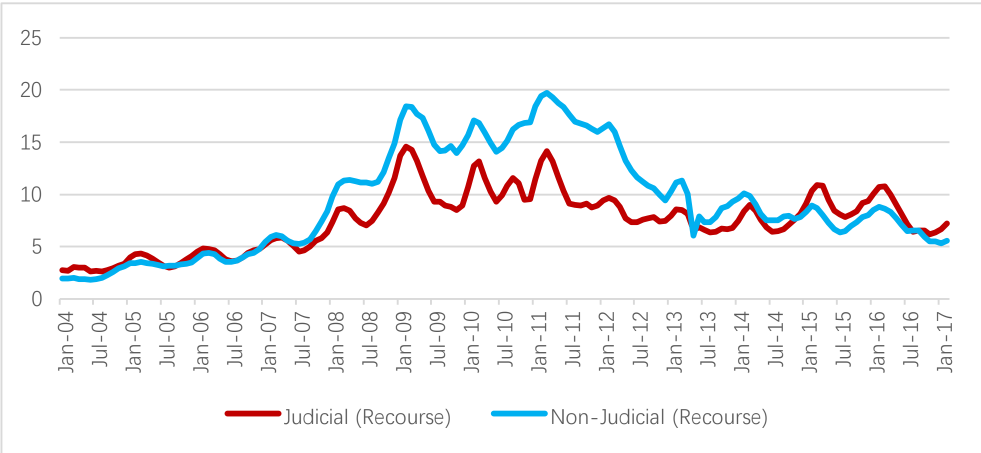
Panel A. The monthly mean value of the MDRI



Panel B The monthly mean value of the HF



Panel C The monthly mean value of the FRS



Note: This figure plots the mean value of different default risk indicators in two subgroups (Judicial and Non-Judicial state group) of the Recourse state group. Panel A, Panel B and Panel C respectively plot the monthly mean value of the MDRI, HF and FRS. The red line and blue line in each panel respectively represent the monthly mean value of the corresponding default risk indicators in Judicial (Recourse) state group and Non-Judicial (Recourse) state group.

Appendix B. Variable definition

Bottom tier house value (BT): Median estimated home value for all bottom-tier homes within a given region. Bottom-tier homes are the homes that fall into the bottom third of home values within a given region. The data is form Zillow's website.

Top tier house value (TT): Median estimated home value for all top-tier homes within a given region. Top-tier homes are homes that fall into the top third of home values within a given region. The data is from Zillow's website.

Mortgage Default Risk Index (MDRI): A real-time index of mortgage default risk indicator proposed by Chauvet, Gabriel and Lutz (2016). The index is calculated on the basis of Google search query data for terms such as "foreclosure help" and "mortgage help". It directly reflects households'concerns about their risk of mortgage default and the possible foreclosure. Compare with the other default risk indicators used in our paper, the MDRI provides an overall reflection of the default risk condition in the home mortgage market. The data is available online, mentioned in the main text.

Homes Foreclosed (HF): The number of homes (per 10,000 homes) that were foreclosed upon in a given month. A foreclosure occurs when a homeowner loses their home to their lending institution or it is sold to a third party at an auction. Compared with the MDRI, the HF only reflect the risk of default ending up with foreclosure procedure, either sold in an auction or become bank-owned properties. The data is available from Zillow's website.

Foreclosure Re-Sales (FRS): The percentage of home sales in a given month in which the home was foreclosed upon within the previous year (e.g. sales of bank-owned homes after the bank took possession of a home following a foreclosure). Similar with the HF, the FRS only reflects the risk of home mortgages end up with foreclosure. The difference between the HF and FRS is that the latter one is restricted to mortgages ending up with foreclosure but not sold via a sheriff's deed or trustee deed. The data is from Zillow's website.