House Price Dynamics and Mortgage Defaults: Theoretical and Empirical Analysis of the Role of Recourse

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Abstract

This paper examines the dynamics of house prices and mortgage defaults in recourse and non-recourse U.S. metropolitan areas. Within an overlapping generations model, we demonstrate that house price shocks result in higher default rates in non-recourse markets. While both markets exhibit negative house price reaction to mortgage defaults, the response is stronger in non-recourse markets. Our findings highlight the critical role of recourse in determining mortgage default and house price risk.

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1. Introduction

The Global Financial Crisis demonstrated the profound impact of mortgage lending on mortgage performance, leading to widespread effects on households, housing markets, financial institutions, and the macroeconomy. Research indicates that the structure of mortgage contracts, particularly whether they are recourse or non-recourse loans, significantly influences household default behavior. The lack of recourse encourages strategic defaults, where borrowers default not due to financial hardship but because the debt exceeds the market value of the house. The inability of lenders to pursue borrowers for any remaining debt beyond the sale price of a foreclosed home increases the risk of default. Using loan-level data, Ghent and Kudlyak (2011) show that the probability of default for underwater borrowers is 1.32 times higher in the absence of recourse. Furthermore, Gerardi et al. (2017) find that strategic motives play a crucial role in mortgage default behavior, as more than 38% of borrowers in default could continue making their mortgage payments without reducing consumption.

Despite extensive studies on borrower behavior, the interdependence between foreclosures and house price dynamics in recourse versus non-recourse markets remains less understood. Calomiris et al. (2013) explored this relationship using a panel vector-autoregressive model of U.S metropolitan areas without discussing recourse. Their findings indicate that while foreclosures negatively impact house prices, the reverse impact is even more significant. This suggests that some borrowers default for strategic reasons, yet their analysis does not focus on the role of recourse. Overall, there remains a gap in our understanding of how house prices interact with defaults in recourse and non-recourse markets.

This paper aims to fill this gap by examining the role of recourse in the house price-mortgage default nexus. We develop an overlapping generations model that incorporates both affordability defaults and strategic defaults. Within this model, we examine the differences between recourse and non-recourse markets in the way house prices interact with defaults. We model household personal income and interest rates as stochastic processes and examine their impact on house prices and defaults under the two regimes. A key feature of our model is that house prices are endogenously determined in a market equilibrium. In a recourse market, households default only for affordability reasons, i.e., when their income is insufficient for them to make their mortgage payments and afford a minimum level of non-housing consumption. In a non-recourse market, there are additional ‘strategic’ defaults by households in negative equity.

We show that after a negative shock to house prices in the non-recourse market, house prices are more likely to fall further when the foreclosed homes of strategic defaulters are sold in the market. For this reason, non-recourse markets experience deeper downturns. However, when fundamentals improve, house prices in both recourse and non-recourse markets recover, and in the long run, they are largely driven by fundamentals. There are instances where house prices in non-recourse markets exceed those in recourse markets due to a shortage in the supply of homes. After a wave of defaults in the non-recourse market, a new cohort of buyers may acquire a sizable fraction of the supply at relatively low prices. This cohort benefits from lower housing costs and is significantly less likely to default. When a new, relatively affluent cohort enters the market, house prices may increase significantly and exceed the level in the corresponding recourse market, especially when borrowing costs are low.

Using Monte-Carlo simulations, we study the dynamics of house prices and defaults in this theoretical framework. We find that the default rate in the non-recourse market is substantially more sensitive to house price shocks relative to the default rate in the recourse market. The response of house prices to shocks in the default rate is also stronger in the non-recourse market, albeit the differences are not that pronounced.

We then test our theoretical predictions using a large set of U.S. metropolitan statistical areas (MSAs) located in recourse and non-recourse states as per the U.S. state recourse classification by Ghent and Kudlyak (2011). We estimate panel vector-autoregressive (Panel VAR) models in annual frequency for the recourse and non-recourse sub-samples of MSAs for the 2000-2019 period. In line with our theoretical framework, we include the appreciation rate of house prices and foreclosures at the MSA level as endogenous variables and the MSA per capita personal income of households and the 30-year mortgage rate as the main fundamental drivers of house prices. In our empirical specification, we also include other widely used determinants of the demand and supply of housing such as the employment rate, population growth, and the industrial production index, as well as sentiment variables related to households' housing market expectations. The empirical results are largely in line with our theoretical predictions and lend support to the described theoretical mechanisms. In particular, a shock to house prices leads to more defaults in non-recourse states, and a shock to the default rate creates a stronger house price response in the non-recourse market in the initial year following the shock. However, the shock of defaults to house prices in the non-recourse market is much stronger in the data than the theory predicts. One potential explanation for this stronger effect is that an increase in the observed defaults leads to expectations of future defaults that are greater in the non-recourse markets where households have strategic reasons to default.

We also conduct an analysis in monthly frequency in which we undertake a more disaggregated investigation by including different house price tiers at the MSA level while also accounting for long-term equilibrium effects. That is, we estimate a panel vector error-correction model (Panel VECM) in which house prices and defaults adjust to a long-term equilibrium. In this alternative setting, the empirical results are consistent with the analysis of the annual data.

While our analysis, as most literature, is motivated by the subprime mortgage crisis, our results also carry implications for current economic and housing market conditions. Our theoretical framework illustrates how house prices adjust to a shock to fundamentals, such as personal income and interest rates, depending on whether mortgages are recourse or non-recourse. Furthermore, by covering the 2000-2019 period, our analysis spans an entire housing market cycle. In that respect, our empirical results have validity beyond the crisis period.

The remainder of this paper is organized as follows. In Section 2, we review the literature on the interaction between house prices and default risk. In Section 3, we present a theoretical model of the role of recourse in the interaction between house prices and mortgage defaults. In Section 4, we describe the methodology and data and in Section 5, we present the empirical results. The concluding remarks are in Section 6.

2. Related literature

The determinants of mortgage default and its interaction with the regional dynamics of house prices are among the most intensely studied topics in the decade following the subprime mortgage crisis. While this literature has employed a multitude of analytical approaches, it can be broadly divided into two strands depending on data sources, level of granularity, research method, questions posed, and the effects explored.

2.1 Micro-level studies

The first strand of literature uses household-level data to examine mortgage default determinants, focusing on strategic default behavior and spillover effects. This literature examines the performance of individual loans (i.e., whether they are in delinquency/default or not) depending on borrower characteristics, loan attributes, and economic and demographic factors prevailing in the local housing market. The major strength of this literature lies in its ability to analyze strategic default behavior and quantify spillover effects. Studies such as Ghent and Kudlyak (2011) and Gerardi et al. (2017) highlight the higher likelihood of defaults in non-recourse states and the significant role of strategic motives.

2.1.1 Strategic default behavior and spillover effects

Strategic default occurs when households default despite being able to make payments, often due to negative equity (Mian and Sufi, 2009; Bradley et al., 2015). Foster and Van Order (1984) view default as an American put option with an exercise price equal to the outstanding mortgage balance. The decision to default is more complicated when one considers additionally the role of the transaction costs of selling the house and the cost of default in this purely financial model. When these aspects are taken into consideration, equity is still an important determinant of default, yet households need to be sufficiently deep in the negative equity territory for strategic default to be advantageous. While Foster and Van Order (1984) do not find empirical support for the purely option-theoretic model, they find that the weaker version of their model that accounts for transaction costs works quite well in explaining the data.

Guiso et al. (2013), Bradley et al. (2015) and Gerardi et al. (2017) discuss factors contributing to strategic default, highlighting the role of social contagion effects. Using survey data from a representative sample of 1,000 American households, Guiso et al. (2013) find that the willingness to default increases in the extent to which households are underwater as measured by the absolute and the relative size of the home-equity shortfall. Furthermore, they find that about 25% of existing defaults are strategic, and that non-pecuniary factors related to fairness and morality, and whether they know somebody who defaults strategically also contribute to the strategic default decision. Hence, social contagion and spillover effects also play a role in the strategic default behavior of households.

Bradley et al. (2015) combine loan-level and local market data from CoreLogic with income data provided by Equifax to examine the performance of over 43 million mortgages. Their definition of strategic default is based on the "double trigger" hypothesis. According to this hypothesis, default is a result of the interaction of negative equity with a "second trigger" caused by adverse life events such as bankruptcy, job loss, divorce, illness, etc.[1] Bradley et al. (2015) differentiate between "distressed defaulters" (borrowers in positive equity unable to pay), "trigger defaulters" (borrowers in negative equity suffering a liquidity shock), and "strategic defaulters" (borrowers in negative equity that do not suffer an income shock). While they find that a lower percentage (8-15%) of mortgage defaults are strategic (between 31,000 and 58,000 out of 400,000 defaults depending on affordability definition) they find evidence for spillovers at the ZIP Code level. In particular, the mortgage delinquency rate and the rate of strategic defaults at the local level are strong predictors for default of individual loans, which

[1] Further tests of the double trigger hypothesis include Cunningham et al. (2021), Elmer and Seeling (1999), Elul et al. (2010), Foote et al. (2008), Mocetti and Viviano, (2017), and Tian et al. (2016).

presents further evidence for spillover effects. Similar spillover effects are also reported by Goodstein et al. (2017) who find that a 1% increase in the local area delinquency rate (i.e., in surrounding ZIP Codes within a 5-mile radius) increases the probability of strategic default by 7.25-16.5%.

Gerardi et al. (2017) develop a novel procedure to assess strategic default by forming household budget sets. Using these budget sets, they identify the households that can continue making mortgage payments without having to substantially reduce their consumption and find that about 38% of mortgage defaults in the Panel Study of Income Dynamics are caused by strategic motives. A second way to identify strategic default is to examine whether households respond to mortgage modification programs. Following the legal settlement with the Countrywide Financial Corporation, beginning in December 2008, Countrywide announced that it will offer loan modification to all delinquent subprime first mortgage loans. Using a difference-in-difference framework to exploit this exogenous change in mortgage modification policy, Mayer et al. (2014) show that this program leads to a 10 percent relative increase in delinquency.

A third way of studying strategic default is by examining how lender recourse impacts default behavior. Ambrose et al. (1997) find that lenders having recourse to assets of borrowers other than the house face a lower incidence of default. Ghent and Kudlyak (2011) show that borrowers in negative equity are more likely to default in non-recourse states, whereby the effect is stronger for owners of high-value homes. Homes in the $500,000-$750,000 value range are twice as likely to be in default in non-recourse states than in recourse states.

Overall, the literature offers ample evidence for strategic default behavior albeit with some differences in the estimated magnitude of the effects. The decline in home values leads to defaults whereby this process is further amplified at the local level due to spillover effects.

2.1.2 The role of expectations

Expectations of house price appreciation significantly influence mortgage product choices and default rates, as demonstrated by Brueckner et al. (2016) and Bailey et al. (2019). Subprime lending played an important role in the housing market crash and the Global Financial Crisis (Mayer et al., 2009). There is a small but growing strand of the literature that examines the interdependence between house price expectations and the use of alternative mortgage products. These mortgage products allow for more flexible repayment including interest-only pay-option adjustable-rate mortgages and negative amortization mortgages (Cocco, 2013; Brueckner et al., 2016). In a model allowing for endogenous backloading and negative amortization, Brueckner et al. (2016) show that expectations of rapid house price appreciation lead to the increased use of alternative mortgage products by borrowers. When house price expectations are favourable, and future price gains are expected by both borrowers and lenders, alternative mortgage products are increasingly used. Analyzing county-level data and using historical house price appreciation as a proxy for price expectations, they find past price appreciation indeed creates a market for alternative mortgage products. However, when house prices decline, alternative mortgage products make borrowers more likely to fall in negative equity leading to defaults and a subsequent housing market crash.

Bailey et al. (2019) combine the results of a market expectation survey conducted by Facebook with Los Angeles residents with data on individual friendship networks on Facebook of over 241 million active users in the U.S. and Canada to construct the house price beliefs of Facebook users. They show theoretically that lower expectations for house price growth lead to higher leverage.[2] A one percentage point decrease in the expected average house price leads to an increase in the loan-to-value ratio by about 11 basis points. The effect of leverage is similar to the effect of alternative mortgage products. It makes the household more likely to fall into negative equity when home values decline and increases the probability of defaults.

Further, based on British Household Panel Survey (BHPS) data for the years 2001, 2007 and 2008, Koblyakova et al. (2014) find that households from regions with low income and low house price to earnings ratio are more likely to choose variable rate mortgage loans, which are more likely to be affected by income and monetary policies.

2.1.3 The impact of mortgage default on house prices

Mortgage defaults negatively impact house prices through increased supply and negative spillover effects. Studies by Campbell et al. (2011) and Mian et al. (2015) quantify these effects. Specifically, mortgage default negatively impacts house prices through two channels. First, mortgage default increases the supply of homes on the market when homes are foreclosed. Second, mortgage default leads to disamenity and other negative spillover effects in local communities. Campbell et al. (2011) estimate a foreclosure discount as high as 27 percent of the average value of a house, which is due to possible damage to the home as well as the lender’s incentive to accept a lower price in order to sell quickly. Mian et al. (2015) use state judicial requirements as an instrument to account for the endogeneity between foreclosures and house prices and find that foreclosures are responsible for about 33% of the decline in house prices during the 2007-2009 period. Recent studies also assessed the negative externality

[2] Given the possibility of strategic default, a borrower is likely to minimise his losses when he makes a smaller downpayment.

caused by neighboring foreclosures. Lin et al. (2009) estimate a price impact of 8.7 percent for properties within 100 meters of the foreclosure and 4.7 percent for properties within 200 meters of the foreclosure. Campbell et al. (2011) find that forced sales due to foreclosure, bankruptcy, or death of the owner result in about 3%-7% discounts on neighborhood house prices. Other studies have also examined the channels through which foreclosures exert downward pressure on prices. Harding et al. (2009) provide evidence of a contagion effect of foreclosure on nearby properties, caused by the negative externality of the foreclosed property which is poorly maintained and neglected in the process of foreclosure. In comparison, Hartley (2014) differentiates between a supply effect and a disamenity effect and finds only the former one to be significant. In a similar vein, Anenberg and Kung (2014) disaggregate the effect on prices into a competition and disamenity effect showing that the latter effect is relevant for high-density low-price neighborhoods.

Alongside foreclosures, alternative methods of property disposition have been increasingly used during the subprime crisis. Clauretie and Daneshvary (2011) explore sales of properties in default through one of the following three options: pre-foreclosure “short sale” by the borrower in default, sales of properties during the foreclosure process by the borrower, or sales of properties as real estate owned (REO) where the foreclosed property is sold by the lender. They find that the short sale has the lowest price discount, but the longest marketing time (see also Biswas et al., 2020). Goodwin and Johnson (2017) find that short sales, similar to REO sales, are sold at a discount, yet short sales are associated with a much longer time on the market. Another strand of the literature compares the spillover effect of short sales, REO properties and foreclosed properties, and finds supporting evidence for the spillover effects of REO and foreclosed properties, but no evidence of negative externality for short sales (Daneshvary et al., 2011; Daneshvary and Clauretie, 2012; Depken et al., 2015).

Considering the high correlation between house prices across regional and national housing markets and with other assets documented in previous studies (see, e.g., Bissoondeeal, 2021; Tsai, 2015), this study also provides new insights for policy makers related to the stability of financial markets and the macroeconomy.

2.2 Macro-level studies

Only a few attempts have been undertaken in the literature to model the dynamic interdependence between house prices, mortgage leverage, and defaults, considering broader economic factors. For instance, Nneji et al. (2013) and Chen et al. (2020) provide frameworks for understanding these relationships, while Gete and Zecchetto (2024) offer a comparative analysis of recourse and non-recourse economies.

Specifically, Nneji et al. (2013) estimate a Markov regime-switching model allowing for a "boom", a "steady state" and a "crash" regime. In line with existing literature, they consider disposable income, long- and short-term interest rates, inflation, unemployment, and economic growth as fundamental variables impacting home values. They show that changes to fundamental variables affect house price dynamics in the "steady state" and "boom" regimes but have no impact during housing busts. Chen et al. (2020) explicitly model the relationship between macroeconomic uncertainty and mortgage refinancing in a structural model of household liquidity management that also accounts for idiosyncratic labor income uncertainty, borrowing constraints, and long- and short-term mortgages. Zabel (2016) views observed house prices and vacancies as deviations from long-run equilibrium. Using an error correction framework, he shows that when there is excess demand, prices rise when vacancies fall, but prices do not fall when there is excess supply and vacancies rise. A summary of this literature is provided in Jones et al. (2016).

Most closely related to the present theoretical analysis is the model by Gete and Zecchetto (2024) which also features non-recourse and recourse mortgage default. Unlike the present model in which the comparison is across metropolitan areas, they compare defaults across two countries (the U.S. and Spain). For that reason, in their setting interest rates, labor supply, and aggregate unemployment are endogenous to the model. These assumptions yield different results. The non-recourse economy (the U.S.) experiences a shorter recession and a faster recovery relative to the recourse economy (Spain).

Most closely related to our empirical analysis is the study by Calomiris et al. (2013) who show that the impact of house prices on foreclosures dominates the impact of foreclosures on house prices. These findings suggest that the strategic choices of homeowners and lenders is important in shaping these bi-directional dynamics. This paper builds on this literature by specifically focusing on the role of recourse in the house price-default nexus, providing novel theoretical and empirical results.

3. Model

In this section we present an equilibrium model of the dynamic interdependence between house prices and mortgage defaults in recourse and non-recourse mortgage markets. The considered framework here shares some of the key features of the mortgage default model of Campbell and Cocco (2015) regarding the modelling of household preferences and the choice of parameters for calibration. The key departure from that model is that house prices in the current setting are endogenously determined and depend on the default decisions of households.

We hereby differentiate between recourse and non-recourse mortgages, considering that in a recourse market household default solely for affordability (liquidity) reasons while in a non-recourse market some households might find it optimal to default strategically. These differences in default behaviour cause differences in the supply of foreclosed homes and alters the equilibrium house price dynamics. The main purpose of the model is to understand the implications of these differences for the house price dynamics under the two mortgage recourse regimes.

3.1 Income process

We consider an overlapping generation setting in which households make decisions over four periods.[3] Time is discrete, measured in years, and indexed by t. In each period t a new generation (of age $a = 0$) of N home buyers enter the housing market. Each home buyer i from this generation receives a stochastic labor income $L_{i,t}^{0}$ which is governed by the process

$$Log(L_{i,t}^{0}) = Log(L_{i,t-1}^{0}) + \nu_t + \epsilon_{i,t}^{0}. \quad (1)$$

Hereby

$$\nu_t = \nu_{t-1} + g + \eta_t$$

is an economy-wide aggregate shock to income affecting households of all generations. The term g signifies the expected income growth and the term η_t is a normally distributed income shock with mean of zero and variance o_{η}^{2}. The component $\epsilon_{i,t}^{0}$ is an idiosyncratic shock affecting only individual household i of age $a = 0$. It is also normally distributed with a mean of zero and a variance of σ_{ϵ}^{2}. Household i decides on the size of the home it wants to buy $H_{i,t}^{0}$ and the amount of its non-housing consumption $C_{i,t}^{0}$ in that period. A unit of housing in that period can be purchased for the price of P_t (to be determined in equilibrium).

In the next period, the home buyers from the previous period are homeowners of age $a = 1$. Each homeowner in that period is exposed to another aggregate and another individual labor income shock. The labor income in that period is

$$Log(L_{i,t+1}^{1}) = Log(L_{i,t}^{0}) + \mathrm{g} + \nu_{t+1} + \epsilon_{i,t+1}^{1} \quad (2)$$

Depending on its realization of income $L_{i,t+1}^{1}$, and the house price P_{t+1}, a homeowner of age $a = 1$ decides whether to default or not to default on his mortgage payment. Mortgage default leads to a foreclosure and it takes one period for a foreclosed home to be sold. Thus, foreclosed homes are sold on the market in the following period when that generation of

[3] Four is the smallest number of periods allowing us to model the decision to buy, to default, for a defaulted home to be foreclosed, and for non-defaulting households to decide to sell their home to relocate for reasons exogenous to the model.

households is of age $a = 2$. While defaulting households of age $a = 2$ leave the market, non-defaulting households remain in their homes for that and the following period when they are of age $a = 3$. We assume that household leave the housing market when they are of age $a = 4$.

3.2. Household preferences and decisions

Following Campbell and Cocco (2015), we assume that every homebuyer i has preferences over its housing consumption $H_{i,t}^{0}$ and a numeraire commodity $C_{i,t}^{0}$ given by the utility function

$$U(H_{i,t}^{0}, C_{i,t}^{0}) = \theta \frac{{H_{i,t}^{0}}^{1-\gamma}}{1-\gamma} + \frac{{C_{i,t}^{0}}^{1-\gamma}}{1-\gamma} \tag{3}$$

where θ measures the importance of housing relative to non-housing consumption and γ is the coefficient of relative risk aversion. Unlike previous literature, we assume that households make this decision in light of their current housing needs and budget constraints. That is, they are not trying to forecast future house prices and are driven entirely by consumption motives. A house of size $H_{i,t}^{0}$ can be bought for $P_t H_{i,t}^{0}$ whereby the purchase can be financed with a fixed-rate mortgage. We assume that each household can borrow at an interest rate of r_t which follows an AR(1) process given by

$$\mathrm{r_t} = \mu(1-\varphi) + \varphi \mathrm{r_{t-1}} + u_{\mathrm{t}} \tag{4}$$

where $\mathrm{r_t} = log(1 + R_t)$ is the log interest rate in period t, μ and φ are parameters to be calibrated and u_t is a normally distributed shock with a mean of zero and a variance of σ_u^2. The household makes a downpayment of $\omega P_t H_{i,t}^{0}$ (using existing savings) and borrows $(1 - \omega) P_t H_{i,t}^{0}$ to purchase the home, where the downpayment to house price ratio ω is exogenously given. We consider a fixed-rate mortgage with a full amortization over a period of K years. That is, for each \$1 borrowed, the household repays

$$m(r_t, K) = r_t \times \frac{(1 + r_t)^K}{(1 + r_t)^K - 1} \tag{5}$$

per year. For convenience, let us to denote the per period repayment cost of a unit consumption of housing by

$$m_t = m(r_t, T)(1 - \omega) P_t.$$

The budget constraint of the household of age $a = 0$ can be written as

$$m_t H_{i,t}^{0} + C_{i,t}^{0} \leq L_{i,t}^{0}. \tag{6}$$

With these preferences and budget constraint, the optimal home size is given by[4]

[4] See Zevelev (2014, p. 73) for the closed form solution of a utility maximization problem with a CES utility.

$$H_{i,t}^{0*} = (\frac{\theta}{m_t})^{\frac{1}{\gamma}} \times \frac{L_{i,t}^0}{(\frac{\theta}{m_t^{1-\gamma}})^{\frac{1}{\gamma}} + 1}.$$

3.3. Defaults

The decision to default depends on whether the mortgage is with or without recourse for the lender. When the mortgage is with recourse, the household defaults only due to a liquidity shock. A liquidity shock is experienced when household income is insufficient to cover the mortgage payment and ensure a minimum (or subsistence) level of non-housing consumption. In non-recourse states, however, we allow households to default for strategic reasons. A strategic default is observed when a homeowner in negative equity finds it preferable to walk away from his investment despite having the requisite income to make the mortgage payment while also meeting his minimum non-housing consumption needs.

Recourse mortgages

In a recourse mortgage contract, the lender can pursue the borrower for any outstanding mortgage balance that is not recouped by the resale of the home. Hence, strategic defaults where households can walk away from their investments even if they can afford the mortgage payment would not occur. Defaults occur only due to liquidity shocks that render the household unable to make the mortgage payment and meet its minimum non-housing needs. Denoting the non-housing subsistence level by $\bar{C}$, a household of age $a = 1$ is in default when the following condition (A) holds

$$L_{i,t+1}^1 - m_t H_{i,t}^0 - \bar{C} < 0 \qquad \text{(A)}$$

Homes of defaulting households are foreclosed and sold in the market in the following period. Thus, the homeownership consumption of household i of age $a = 1$ is $H_{i,t+1}^1 = H_{i,t}^{0*}$ when the household has not defaulted and zero when the household has defaulted.

Non-recourse mortgages

In a non-recourse mortgage contract, the lender cannot pursue the borrower for any debt exceeding the value of the home. Hence, when the borrower is significantly 'underwater,' i.e., when the value of the home falls substantially below the outstanding mortgage balance, the household may find it optimal to walk away from its investment. The equity that a household of age $a = 1$ has in its home at time $t + 1$ is

$$W_{i,t+1}^1 = P_{t+1} H_{i,t}^0 - (1 - \omega) P_t H_{i,t}^0 [1 - (m(r_t, T) - r_t)]$$

Hereby the first term is the value of the house in period $t + 1$, and the second term is the outstanding mortgage balance after one repayment period. As default is associated with loss of access to future borrowing as well as reputational and psychological costs, we assume that strategic default occurs when the household's negative equity exceeds a certain threshold relative to its income. That is, the household defaults strategically when

$$W_{i,t+1}^{0} < -\delta L_{i,t+1}^{1} \tag{S}$$

where $\delta > 0$ is the strategic default parameter. Similarly, household i of age $a = 1$ consumes $H_{i,t+1}^{1} = H_{i,t}^{0*}$ when the household is not in default (both (A) and (S) are not satisfied) and zero when the household has defaulted.

3.3. Housing market equilibrium

We assume that supply in the housing market is inelastic and normalized to $S = 1$, and in each period four cohorts of households (of ages $a = 0,1,2$ and 3) coexisting in the housing market. The price of a unit of housing P_t is determined in a partial market equilibrium in which aggregate demand corresponds to supply, $D(P_t) = S$ in each period t. Aggregate demand is composed of the demand of the four cohorts

$$D(P_t) = H_t^0(P_t) + H_t^1(P_{t-1}) + H_t^2(P_{t-1}, P_{t-2}) + H_t^3(P_{t-2}, P_{t-3})$$

The demand of the cohort of age $a = 0$ is given by

$$H_t^0(P_t) = \sum_{i=1}^{N} H_{it}^{0*}(L_{it}, P_t)$$

where H_{it}^{0*} is the solution of the consumer maximization problem (1) under budget constraint (2). Cohort $a = 1$ of households have purchased their homes in the previous period and their demand is given by

$$H_t^1(P_t) = \sum_{i=1}^{N} H_{i,t-1}^{0*}(L_{i,t-1}, P_{t-1})$$

Cohort of age $a = 2$ have purchased two periods ago and some of them have defaulted in the previous period. Their aggregate demand is given by

$$H_t^2(P_t) = \sum_{i=1}^{N} H_{i,t-2}^{0*}(L_{i,t-2}, P_{t-2}) \times ND(L_{i,t-1}, P_{t-1}, P_{t-2})$$

where $ND(L_{i,t-1}, P_{t-1}, P_{t-2})$ is an indicator taking on the value of 1 if the household has not defaulted, and zero otherwise. Cohort $a = 3$ is defined analogously to cohort 2 and consists of households who bought three periods ago and have not defaulted when they were of age $a =$ 1.

3.4. Model predictions

We begin the analysis with the derivation of two general predictions. It is useful to denote the areas of affordability default (A) and strategic default (S) as illustrated in Figure 1.

[Insert Figure 1 around here]

Proposition 1a. (Strategic and affordability default). *A negative house price shock generates more defaults in the non-recourse market than in the recourse market.*

Proof. Let us denote the area of affordability default by A and strategic default by S in the home equity - income graph (W, L) as illustrated in Figure 1. Let us assume that we observe a sufficiently strong downward movement of home values so that $P_{t-1} < P_{t-2}$ and $W_{i,t-1}^{1} < 0$. For a given $W_{i,t-1}^{1}$, the probability of default in a non-recourse state is given by the probability that the realization of income would be either in area A or in area S. In a recourse market, default occurs only when the income realization is in area A. Hence, more defaults are observed in the non-recourse market. □

Proposition 1b. (Downward momentum). *A negative house price shock creates a stronger downward momentum (i.e., the possibility for a further and stronger house price decline) in the non-recourse market than in the recourse market.*

Proof. We need to show that if $P_{t-1} < P_{t-2}$ and $W_{i,t-1}^{1} < 0$, the next period price in a non-recourse market would be lower: $P_t^{NR} \leq P_t^{R}$. As in a non-recourse market some agents of age $a = 2$ would be strategic defaulters, we will have less defaults in recourse markets: $ND^{R}(L_{i,t-1}, P_{t-1}, P_{t-2}) \geq ND^{NR}(L_{i,t-1}, P_{t-1}, P_{t-2})$ and hence more supply of homes from households of age $a = 2$, i.e. $H_t^{2,R}(P_t) \geq H_t^{2,NR}(P_t)$. It follows that $D^{R}(P_t) \geq DN^{R}(P_t)$ and hence $P_t^{NR} \leq P_t^{R}$. □

3.5. Simulation

Further insights into the model predictions can be obtained from simulating the price formation and the default processes in recourse and non-recourse states. We analyze data obtained from a Monte-Carlo simulation for $T = 10{,}000$ periods and $N = 5$ groups of agents entering the market each period. We assume that households default strategically when their negative equity exceeds their annual labor income (i.e., the default parameter is $\delta = 1$) and that the loan-to-value ratio of home buyers is 95% (i.e., $\omega = 0.05$). The remaining parameters of the model are set to the values calibrated by Campbell and Cocco (2015) as shown in Table 1.

[Insert Table 1 around here]

We initialise the model by assuming that there are no defaults in the first four periods. The household income in the initial periods is $L_{i,t}^{0} = 1$ for $t = 0,1,2,3$ and the interest rate in these periods is set to its long-term average of $\mu = 0.012$ which yields a mortgage rate of $m_t = 3.99\%$. Thus, the equilibrium price in the first two periods is

$$P_1 = P_2 = \frac{4N\theta}{(1-\omega)m_1} = 158.33.$$

An example of the equilibrium path of house prices for the simulation of the first 30 periods is given in Figure 2.

[Insert Figure 2 around here]

The figure visualizes several key properties of the simulation. First, long-term house prices in recourse and non-recourse states do not significantly deviate from each other and are generally governed by the fundamental factors in the model: household income and interest rates. The short-term dynamics, however, differs in recourse and non-recourse markets. Consider a negative shock to fundamental variables which leads to decline in home values. The same decline in home values creates more defaults in the non-recourse market as some home buyers default strategically. This effect leads in the following period to a more pronounced decline in home values in non-recourse states relative to recourse states. This trend, however, is short lived. When foreclosed homes in the non-recourse market are bought at low prices by a new cohort of buyers, this cohort occupies a large fraction of the supply and is less likely to default either for strategic or affordability reasons. Indeed, this cohort creates a shortage of homes for the following cohorts entering the non-recourse market. Hence, following several periods of declines, house prices recover faster in the non-recourse market, and, as shown in Figure 2, due to the lack of supply they might even temporarily exceed the prices in the recourse market.

Using the data from the Monte-Carlo simulation, we also estimate the following Vector Auto-Regressive (VAR) model

$$\begin{pmatrix} \Delta MT_t \\ \Delta DR_t \end{pmatrix} = \boldsymbol{A_0} + \sum_{j=1}^{p} \boldsymbol{A_j} \cdot \begin{pmatrix} \Delta MT_{t-j} \\ \Delta DR_{t-j} \end{pmatrix} + \boldsymbol{B} \cdot \begin{bmatrix} \nu_t \\ r_t \end{bmatrix} + \boldsymbol{\varepsilon_t} \tag{7}$$

where $\Delta MT_t = Log(P_t) - Log(P_{t-1})$ is the house price appreciation rate, ΔDR_t is the percentage of homeowners in default, ν_t is the permanent shock to income and r_t is the realized interest rate in period t. Hereby $\boldsymbol{A_0}$ is a vector of intercepts, $\boldsymbol{A_j}$ are a 2×1 diagonal matrices of coefficients to be estimated, and $\boldsymbol{B}$ is a vector of the coefficients for the fundamental variables to be estimated. The results from the simulation are represented alongside our panel data empirical results for comparison purposes. The Granger causality tests, presented in Table 3 (see the results for the VAR model) show a bi-directional causality both in the recourse and the non-recourse market. The forecast variance decomposition, represented in Table 7 (see the Panel A. VAR specification), shows that innovations in the default rate and in the house price growth rate explain a greater percentage of the variance in the house price growth rate and the default rate in non-recourse states, respectively. These effects are also visible in the impulse response functions presented Figure 5 (see the Panel A: VAR using simulated data specification). A shock to defaults leads to a greater house price decline in the non-recourse market. This response reverses in the next period as the upcoming cohort purchases the foreclosed homes at low prices and is thus less vulnerable to default. In recourse states, in contrast, the effect of house prices on defaults is very small. Thus, a negative house price shock precipitates a wave of defaults in the non-recourse market but has only a small impact on defaults in the recourse market (left panel in Figure 5). The responses of house prices to defaults are of a similar magnitude across recourse and non-recourse states and illustrate the equilibrium adjustment of house prices due to the supply of foreclosed homes in the market (right panel in Figure 5).

3.6. Discussion

There are several recent attempts to model the endogenous relationship between house prices and defaults. Guren and McQuade (2020) introduce the aspect of mortgage lending and consider a setting in which default negatively impacts the balance sheet of lenders when they sell foreclosed homes at a discount. This effect leads to credit rationing for new home buyers and lowers the demand for homes further exacerbating housing downturns. Chatterjee and Eyigungor (2009) consider a non-recourse market in which underwater households default and move to the rental market. This process leads to a downward spiral of house prices, yet a government prevention policy of forbearance and loan modification (with features like the Home Affordable Modification Program of 2009) can stabilize prices.

Most closely related to the present setting is the model by Gete and Zecchetto (2024) who examine the house price dynamics in a recourse and a non-recourse economy (US and Spain, respectively). As they conduct an analysis at a national level, they also endogenize the labour income and interest rate processes while identifying a crisis as a shock to labor productivity. In their model, household debt has a negative impact on aggregate non-housing consumption. As the economies recover from the shock, households in the non-recourse economy increase consumption more as their debt is written off. This effect stimulates growth and consequently the non-recourse economy recover more rapidly and the downturn in house price is less severe (see Figure 8 on page 1078 therein). This prediction runs counter the result of our current model yet, similarly to our setting, these effects are transient, and house prices in both economies recover after about four years.

There are several key assumptions in our model which drive our model predictions. First, households are guided solely by their current consumption motives when they decide on the size of homes they buy. They are not trying to predict future house prices or interest rates and time the market. Second, the home ownership and the rental markets are sufficiently segmented so that households which default create only a supply effect when their homes are foreclosed and sold in the market. They do not create additional demand when they migrate to the rental market (see, e.g., Guren et al. 2021 for a similar assumption and Chatterjee and Eyigungor 2009 for a setting accounting for the rental market). Finally, local house prices are determined in equilibrium and depend on labor income and interest rates which are exogenously given. Although it provides only a stylized depiction of recourse and non-recourse markets, the model generates testable predictions which we examine in our empirical analysis.

4. Methodology, data and descriptive statistics

The main objective of this study is to explore the dynamic interdependence between house price appreciation rates and mortgage default rates in recourse and non-recourse markets. We begin the analysis by estimating an empirical specification with annual data that is closely related to our theoretical model. As a second step, we use monthly data and analyze empirical models which additionally account for potential long-term cointegrating relationships among the endogenous variables.

4.1. Annual data

We analyze a sample of 236 MSAs from 31 U.S. states, classified into recourse and non-recourse markets based on Ghent and Kudlyak (2011). This classification divides U.S. states into recourse and non-recourse ones depending on how easy it is for lenders to obtain a deficiency judgement against borrowers if the foreclosure sale does not fully recover the mortgage debt. Recourse and non-recourse MSAs are metropolitan areas located in recourse and non-recourse states, respectively. As we study the effect of recourse, we focus on the non-judicial U.S. states. In these states the foreclosure process does not require a court order. That is, lenders can foreclose on properties without having to file a lawsuit if the mortgage includes a power of sale clause.[5] This allows us to focus on the default risk attributable to recourse rather

[5] Judicial states are states with regulations requiring lenders to go through a lengthy judicial foreclosure process (Mian et al. 2015). In these states there is a substantial delay from the default to the sale of the foreclosed property.

than to the foreclosure procedure in the state. The states included in our sample, along with their classification are shown in Table 2. The classification yields 140 recourse and 96 non-recourse MSAs that we use in our analysis. A map of U.S. states with the location of these MSAs is represented in Figure 3. Our study covers the 2000-2019 period. Our main variables include Zillow's middle-tier house price indices, CoreLogic's mortgage default rates, and many macroeconomic and demographic controls from various sources.

[Insert Table 2 and Figure 3 around here]

4.1.1 House prices

We use Zillow's middle-tier (*MT*) house price indices to measure annual appreciation rates of a typical home in each MSA.[6] Starting from January 2023, Zillow produces tiered indices using the 'neural Zestimate.' The Zestimate is a value estimate for individual properties produced regularly regardless of whether there is an underlying transaction on the property or not. The Zestimate is based on a machine learning algorithm relying on neural networks trained on the history of property data including sales transactions, tax assessment and public records, but also home details such as square footage and location. We measure the annual appreciation for each year as the difference of the logarithms of the price index for December of each year.

4.1.2 Default rates

We measure mortgage default risk (*DR*) by the proportion of loans undergoing foreclosure relative to the total number of outstanding first lien loans. The data is obtained by the MarketTrends dataset provided by the CoreLogic Servicing and Securities products in monthly frequency. This dataset covers approximately 85% of the number of loans outstanding and the associated loans in foreclosure process in metropolitan areas. Hereby foreclosure is defined as the legal process by which an owner's right to a property is terminated usually due to default. To obtain annual values for the proportion of loans in foreclosure, we take the monthly average.

4.1.3 Macroeconomic and demographic control variables

In accordance with our theoretical framework, we also control for the impact of macro-economic and demographic factors on the demand and supply of homes. In particular, we include the per capita personal income and the population in each MSA, which are obtained from the Bureau of Economic Analysis (www.bea.gov). In line with our theoretical framework, we also include the 30-year U.S. mortgage rate from FRED (https://fred.stlouisfed.org/) in weekly frequency and average over all weeks in each year to obtain the annual average rates.

Using the classification by Mian et al. (2015), we excluded the judicial states from the analysis as the foreclosure process might have an impact on default risk.

[6] These time series are downloaded from https://www.zillow.com/research/data/.

As further controls we include the number of total nonfarm payroll (*Employment*), the new private housing units authorized by building permits (*Permit*), the industrial production index (*INDPRO*), the producer price index for all commodities (*PPIACO*), and the University of Michigan consumer sentiment (*UMCSENT*), from different sources and all of which are obtained from FRED. Employment and building permits are observed at the MSA level and state level, respectively, while the production index, the producer price index, and the consumer sentiment are available at the national level. Finally, to control for the stock market, we include the S&P 500 Index (*SP500*) which is obtained from Yahoo Finance. The definitions for all variables are presented in Table 3, and the descriptive statistics of all these variables in annual frequency, along with stationarity tests, are presented in Table 4.

[Insert Table 3 and Table 4 around here]

4.1.4 Panel VAR model

We begin with an empirical specification that matches our theoretical framework. For the theoretically simulated data, the equilibrium default rate and the house price appreciation rate variables are stationary. We thus estimate a vector autoregressive model with these two endogenous variables while including all the exogenous control variables mentioned above. To account for the panel structure of our empirically observed data and considering that we have a relatively short panel of annual data, we estimate a Panel Vector Auto-Regressive (Panel VAR) model as described by Holtz-Eakin et al. (1988). This approach allows us to examine the short-run dynamic interaction between house prices and mortgage defaults while controlling for the macroeconomic environment. Our empirical model is specified as follows[7]

$$\Delta \boldsymbol{Y}_{i,t} = \begin{pmatrix} \Delta MT_{i,t} \\ \Delta DR_{i,t} \end{pmatrix} = \sum_{j=1}^{p} \boldsymbol{A}_j \cdot \Delta \boldsymbol{Y}_{i,t-j} + \boldsymbol{B} \cdot \boldsymbol{X}_{i,t} + \boldsymbol{\varepsilon}_{i,t} \tag{8}$$

where p is the order of VAR, $i = 1,2,\dots,N$ denotes the metropolitan statistical area and $t = 1,2,\dots,T$ denotes the year. The vector $\Delta \boldsymbol{Y}_{i,t-j}$ contains the endogenous variables, which include the appreciation rates of the middle tier homes $\Delta MT_{i,t} = \log\left(MT_{i,t}\right) - \log\left(MT_{i,t-1}\right)$ and the change in the default rate $\Delta DR_{i,t} = DR_{i,t} - DR_{i,t-1}$. The vector $\boldsymbol{X}_{i,t}$ represent the previously defined macroeconomic control variables. We use $\boldsymbol{\varepsilon}_{i,t}$ to denote the vector of the white noise error terms. We estimate the Panel VAR system with one lags ($p = 1$), which is the optimal number of lags determined by the Bayesian information criterion.

[7] A vector autoregressive model with a similar structure, where exogenous variables enter in the regression equation contemporaneously, has been analyzed by Yan et al. (2016). The panel specification we use here takes also into account the cross-sectional dependence across MSAs. We have confirmed the system stationarity of our model via checking the eigenvalue of the companion matrix.

In the presence of lagged dependent variables in the model, the commonly used least squares estimator will be biased even when the sample size is large (Judson and Owen, 1999). Therefore, following Arellano and Bover (1995) and Love and Zicchino (2006), we estimate the coefficients $\boldsymbol{A}_j$ and $\boldsymbol{B}$ using the Generalized Method of Moments (GMM), with the lags of the endogenous variables used as instruments. Furthermore, following the method of Abrigo and Love (2016), we apply a Helmert transformation to control for the MSA fixed effects. We report Granger causality tests, impulse response functions, and forecast error variance decompositions for the bidirectional relationship between default risk and housing returns.

4.2. Monthly data

For long-term equilibrium relationships, we collect monthly data for the variables used in Panel VAR regression. Furthermore, to model the process of equilibrium adjustments of different segments of the housing market, we also include the Zillow bottom-tier (*BT*) and top-tier (*TT*) house price indices as endogenous variables. They capture the price dynamics of homes in the 5^{th}-35^{th} and 65^{th}-95^{th} percentile ranges, respectively, in each of the metropolitan statistical areas. The descriptive statistics of all these variables in monthly frequency, along with stationarity tests are presented in Table 5. The dynamics of monthly middle-tier house prices along with the appreciation rates, and the dynamics of the average default rate across the U.S. within the sample period are shown in Figure 4.

[Insert Table 5 and Figure 4 around here]

4.2.1 Panel VECM model

We test for long-term cointegration among house price tiers and default rates, proceeding with a Panel VECM model based on significant co-integration test results. As panel co-integration tests (Pedroni, 1999) provide strong evidence for co-integration, we proceed by estimating the following panel vector error correction model (Panel VECM)

$$\Delta \boldsymbol{Y}_{i,t} = \begin{pmatrix} \Delta TT_{i,t} \\ \Delta MT_{i,t} \\ \Delta BT_{i,t} \\ \Delta DR_{i,t} \end{pmatrix} = \sum_{j=1}^{p} \boldsymbol{A}_j \cdot \Delta \boldsymbol{Y}_{i,t-j} + \boldsymbol{\alpha} \cdot ECT_{i,t-1} + \boldsymbol{B} \cdot \boldsymbol{X}_{i,t} + \boldsymbol{\varepsilon}_{i,t} \tag{9}$$

The $\Delta TT_{i,t}$, $\Delta MT_{i,t}$, $\Delta BT_{i,t}$ denote the appreciation rate of the three price tiers and the $\Delta DR_{i,t}$ is the change in the default rate. The error correction terms $ECT_{i,t}$ are determined as the residuals $u_{i,t}$ from the following fixed effects regression,

$$DR_{i,t} = \beta_{TT} log(TT_{i,t}) + \beta_{MT} log(MT_{i,t}) + \beta_{BT} log(BT_{i,t}) + Time_t + \delta_i + u_{i,t}.$$

That is, the error correction term is determined by the equation,

$$ECT_{i,t} = DR_{i,t} - [\hat{\beta}_{TT} log(TT_{i,t}) + \hat{\beta}_{MT} log(MT_{i,t}) + \hat{\beta}_{BT} log(BT_{i,t}) + \widehat{Time}_t + \hat{\delta}_i].$$

Hereby $\hat{\beta}_{TT}$, $\hat{\beta}_{MT}$ and $\hat{\beta}_{BT}$ are the coefficients of the cointegrating equation. The 4×1 vector of the speed of adjustment coefficients $\boldsymbol{\alpha} = (\alpha_{TT}, \alpha_{MT}, \alpha_{BT}, \alpha_{DR})$ in equation (9) is obtained as the coefficients of the error correction term in the Panel VECM regression. The control variables *Income* and *Population* contained in the vector $\boldsymbol{X}_{i,t}$ are not available in monthly frequency. We, therefore, consider a specification without these variables, and a specification in which we interpolate the missing data for these variables.[8] We estimate the Panel VECM system with 5 lags ($p = 5$), which is the optimal number of lags determined by the Bayesian information criterion.

5. Results

To facilitate the comparison between theoretical and empirical results, we present the estimates of a VAR model for the simulated data, of the Panel VAR model for the annual data, of the Panel VECM model for the monthly data. Our results are based on Granger causality tests, impulse response analysis, and forecast error variance decompositions.

5.1 Granger causality tests

The Granger causality tests for the interaction between middle-tier house price appreciation rates and mortgage default risk are reported in Table 6. The columns in *Panel A: ΔMT → ΔDR* report the test results for the null hypothesis that house price returns do not Granger-cause mortgage default, while the columns in *Panel B: ΔDR → ΔMT* report the test results for the null hypothesis that mortgage default does not Granger-cause house price returns. As indicated, VAR, Panel VAR and Panel VECM are based on the simulated annual data, actual annual data and actual monthly data, respectively. The *, ** and *** asterisks indicate a rejection of the null hypothesis at 10%, 5% and 1% significance level, respectively.

[Insert Table 6 around here]

The results in Panel A, based on actual data, provide evidence for Granger causality running from house price returns to mortgage defaults mainly in non-recourse markets. These results are consistent with the notion that borrowers have less incentives to default in recourse markets.[9] Indeed, the null hypothesis that house price returns do not Granger cause mortgage default is rejected either at the 5% or 1% significance levels for all models. In comparison, in recourse states, the null hypothesis is only rejected at 10% significance level in the result of

[8] For the interpolation we assume that the monthly growth rate of income and population are the same for all months during the year and are chosen so as to correspond to the annual growth rate for the year in each MSA.
[9] In the simulated data, a bi-directional Granger causality is observed. This effect is most likely due to the permanent income shock ν_t which affects multiple cohorts of homeowners.

Panel VAR model for the annual data. These results are consistent with the theory of option theoretic (or strategic) default: borrowers in non-recourse states are more likely to walk away from their investment when house prices decline, and they fall into negative equity.

Panel B shows that default risk Granger causes house price return rate both in recourse and non-recourse states. In most of the Granger causality tests, the null hypothesis that mortgage default does not Granger cause house price depreciation rate is rejected at the 1% significance level. These findings are expected due to both direct market equilibrium effects and externalities. That is, house prices decline because foreclosed homes increase the housing supply in the market, and because of spill-over and disamenity effects caused by mortgage default (Campbell et al., 2011; Anenberg and Kung, 2014).

5.2 Impulse response functions

In this section, we analyze generalised impulse response functions (GIRF)[10] to quantify the effect of house price return on the future dynamics of mortgage default and the effect of mortgage default on the future dynamics of house price returns.

[Insert Figure 5 around here]

Figure 5 presents the GIRFs of the mortgage default rate to a one standard deviation shock to house price return (left panel) and the response of the middle-tier house price return to a one-standard-deviation positive[11] shock to the mortgage default rate (right panel). The 95% confidence intervals represented in the graphs are based on a Monte Carlo simulation. Panels A, B, C, and D show the GIRFs generated from the estimates of the VAR, Panel VAR and Panel VECM with and without interpolated data.

Panel A of Figure 5 shows the impulse responses of the change of mortgage default rate and house price return rate based on the VAR regression using simulated annual data. The response of the mortgage default rate for a one-year horizon is negative and significant. It is notably stronger in the non-recourse market than in the recourse market. For a two-year horizon the response is positive and significant in the non-recourse market, and close to zero in the recourse market. For the three-year horizon and beyond, the impulse responses in both markets tend to converge to zero.

The impulse response results shown in Panel B of Figure 5 are based on the Panel VAR regression using actual annual data. There are a few notable similarities between simulated

[10] Generalised impulse response functions, proposed by Pesaran and Shin (1998) have the advantage over the traditional impulse response functions, obtained by the orthogonal decomposition of the error covariance matrix, in that they are invariant to the ordering of variables in VAR (see, e.g. Lütkepohl, 2005, p.61, for the criticism of the traditional approach).

[11] By construction, the effect of a one-standard-deviation negative shock has the same size and the opposite sign.

results and the results obtained with the actual data. In the actual data, the response of the mortgage default rate to a shock to the house price return for a one-year horizon is significantly stronger in non-recourse states as has been the case for the simulated data. The graph in Panel B (right) also shows that the response of the house price returns to shocks in the mortgage default rate are significantly stronger in non-recourse states than in recourse states. The differences are statistically significant for the first five years after the shock.

Panels C and D represent the impulse responses based on Panel VECM regression using monthly data. The results in both panels show that the responses of both variables are significantly stronger in non-recourse states than in recourse states within the 60-month forecast horizon. The responses reach their highest absolute value within the first year after the shock and tend to converge to zero in the long run in both recourse and non-recourse states. Considering that these panels are estimated in monthly frequency, the results are in line with the annual data results presented in Panels A and B.

Overall, the GIRFs indicate that shocks to house price returns lead to stronger responses in mortgage default rates in non-recourse markets. Similarly, shocks to mortgage defaults result in more pronounced declines in house prices in non-recourse markets, corroborating our theoretical predictions. These effects also corroborate the results of Ghent and Kudlyak (2011) derived from loan-level data, who report that borrowers are 30% more likely to default in non-recourse states.

5.3 Forecast error variance decompositions

We further examine forecast error variance decompositions (FEVD) to quantify the relative importance and strength of the bi-directional impacts between house price returns and mortgage default risk. As with the impulse response analysis, we use the middle house price tier to represent the housing market. The left columns in Table 7 show the percentage of the forecast error variance of the mortgage default rate due to innovations in housing returns. The VAR and Panel VAR rows represent the variance decompositions for the simulated and actual data, respectively, for 2, 4, 6, 8, and 10-year-ahead forecast horizons. The Panel VECM in Panel C and D report the variance decomposition results for 12, 24, 36, 48, and 60-month-ahead forecast horizons. The 2nd and 3rd columns report the percentage of forecast error variance of the change in the mortgage default rate explained by house price return innovations in recourse and non-recourse states, respectively. The 4th and 5th columns report the percentage of forecast error variance of the house price return rate explained by innovations in the default rate.

[Insert Table 7 around here]

Table 7 shows that the bidirectional impacts between house prices and mortgage defaults is stronger in non-recourse states. This result holds true for both directions of impact and is robust across specifications. For example, the results in Panel C based on the Panel VECM regression with monthly data and all exogenous control variables, show that, at the 60-month-ahead forecast horizon, the forecast error variance of the mortgage default rate that can be explained by innovations in the house price returns is 4.32% in recourse states and 10.51% in non-recourse states. Similarly, for the same forecast horizon, 1.46% and 7.32% of the forecast error variance of house price returns can be explained by innovations in mortgage default in recourse and non-recourse states, respectively. In Panels A, B, and D based on all other regression specifications and control variable settings considered, we also observe that the effect of shocks is stronger in the non-recourse markets. Overall, the forecast error variance decompositions show that the bidirectional impacts between house prices and mortgage defaults are stronger in non-recourse states, highlighting the significance of strategic defaults in these markets. Our results speak to the potential of option-based theories of default to explain household behavior and market reaction to declines in house prices among homeowners. Furthermore, we show that the equilibrium adjustments of house prices to shocks in defaults are stronger in non-recourse states. To the best of our knowledge, these effects are novel and have not been discussed in the prior literature. Given that these results are observed in the actual and not in the simulated data point to the role of household expectations as a potential explanation for the effects.

5.4 Panel VECM results

We turn now to the analysis of monthly data. As it constitutes a much longer panel, we first test for the existence of a long-run equilibrium between the three price tiers and the default rate. The Pedroni (1999) panel co-integration tests provide multiple statistics to evaluate the presence of co-integration. These statistics include the panel v-statistic, panel rho-statistic, panel t-statistic, and panel ADF-statistic, as well as group-specific versions of these tests. The null hypothesis for these tests is that there is no co-integration among the variables. Rejection of the null hypothesis indicates the presence of a long-term equilibrium relationship. In Table 8 we report the results of Pedroni (1999) panel co-integration tests.

[Insert Table 8 around here]

Both in the recourse and the non-recourse market, at least three of the statistics indicate a rejection of the null hypothesis of no cointegration at the 1% statistical level. We thus conclude that both markets are bound by a long-run relationship. These findings collectively confirm that there is a robust long-term equilibrium relationship between the house price tiers and the default rate in both recourse and non-recourse markets. The presence of co-integration suggests that despite short-term fluctuations, house prices and default rates are bound by a stable long-run relationship, adjusting over time to maintain equilibrium.

The significant co-integration results in both market types highlight the dynamic interplay between house prices and default rates. In recourse markets, the long-term relationship indicates that house prices and default rates are tightly linked, with defaults primarily driven by affordability issues. In non-recourse markets, the co-integration results suggest that strategic defaults significantly influence the long-term behavior of house prices. The higher sensitivity of default rates to house price changes in non-recourse markets underscores the role of strategic default behavior, where borrowers are more likely to default when house prices fall significantly below the mortgage balance.

We proceed with the estimation of a Panel VECM model. The estimated coefficients are reported in Table 9.

[Insert Table 9 around here]

In recourse markets, there is a significant negative long-run cointegrating relationship between the top tier house index and defaults, while in non-recourse markets there is a significant negative cointegrating relation between both the top tier and the middle tier indices and defaults. The signs and the significance levels of the error correction coefficients α_{ECT} show evidence for adjustment towards the long-run equilibrium in both markets. The adjustment processes, however, are different. In recourse markets, when the default rate is above its long-run equilibrium, the middle tier and the top tier house prices decline to restore the long-run relationship. In the non-recourse market, on the other hand, when the default rate exceeds its long-run equilibrium value, it adjusts downwards toward its equilibrium value. These results show that defaults are more sensitive to shocks in non-recourse states, consistent with strategic default behavior.

Overall, the Panel VECM results indicate significant long-run cointegration relationships between house price tiers and default rates. The adjustment processes differ between recourse and non-recourse markets, with defaults more sensitive to shocks in non-recourse states. The coefficients for the short run dynamics provide some evidence of house price momentum and reversal which applies mostly to the top and the middle tier. A higher appreciation of the tiered index in the current month makes the index more likely to appreciate in the following month but less likely in the month thereafter. These momentum effects in the dynamics of the tiered house price indices are consistent with prior literature (see, e.g., Damianov and Escobari, 2016).

6. Conclusion

This paper examines the interaction between house prices and mortgage defaults in recourse and non-recourse markets. Our theoretical and empirical analyses demonstrate that house price shocks generate more defaults in non-recourse markets due to strategic default behavior. Empirical results from a Panel VAR model confirm these predictions, while also showing stronger response of house prices to mortgage defaults in non-recourse states.

Our analysis is based on an overlapping generations framework in which house price appreciation and default rates are determined in a market equilibrium and depend on fundamental factors such as household income and interest rates. In a recourse market, households default solely for affordability reasons, while in a non-recourse market some households default strategically. We examine how these differences impact the dynamics of house prices and mortgage defaults.

The analysis of a vector-autoregressive model (VAR) estimated with a (Monte Carlo) simulated data from our theoretical model shows — consistent with the theoretical analysis — that a negative house prices shock generates more defaults in the non-recourse market as some households default for strategic reasons. Estimating a Panel VAR model for a large panel of recourse and non-recourse MSAs, we confirm this prediction also empirically. The difference in defaults between recourse and non-recourse markets in response to a house price shock is statistically significant for the first year after the shock, both in our theory and in the data. The same result obtains when estimating a Panel VECM model in monthly frequency.

Simulated data show that the response of house prices to a mortgage default shock is comparable across recourse and non-recourse states, with the response in the non-recourse market being stronger. Our econometric analysis of both annual and monthly data confirms this prediction while revealing even stronger effect on prices in non-recourse markets. Shocks to mortgage default leads to a significantly lower house price appreciation in the non-recourse markets which lasts for several years. One potential explanation for this finding is that in a non-recourse market, both buyers and sellers anticipate further future defaults following price declines, and these default expectations depress home values for a prolonged period.

By quantifying the differences in mortgage defaults and house price dynamics across recourse and non-recourse markets, our results carry implications for households and mortgage lenders, as well as policy makers and market regulators.

Table 1. Calibration of parameters

Parameter	Value	Interpretation	Source
Household preferences			
θ	0.3	Importance of housing consumption	CC 2015
γ	2.0	Coefficient of relative risk aversion	CC 2015
Labor income			
g	0.080	Mean log real income growth	CC 2015
σ_η	0.063	St. dev. of permanent income shock	CC 2015
σ_ε	0.225	St. dev. of idiosyncratic transitory income shock	CC 2015
Interest rate			
μ	0.012	Mean value of the AR (1) process	CC 2015
φ	0.825	Autoregressive term	CC 2015
σ_ε	0.009	St. dev. of interest rate shock	CC 2015
Downpayment			
ω	0.05	Downpayment as a percentage of home value	
Mortgage repayment period			
K	30	Years of repayment with full amortization	
Default			
$\bar{C}$	0.1	Subsistence non-housing consumption level	
δ	1.0	Strategic default parameter	

Notes: This table reports the calibrated parameters used in the overlapping generations model, and CC 2015 means that this parameter is sourced from Campbell and Cocco (2015).

Table 2. Classification of states

States	Recourse/Non-recourse	States	Recourse/Non-recourse
Alabama	Recourse	**New Hampshire**	Recourse
Alaska	Non-recourse	**North Carolina**	Non-recourse
Arizona	Non-recourse	**Oklahoma**	Recourse
Arkansas	Recourse	**Oregon**	Non-recourse
California	Non-recourse	**Rhode Island**	Recourse
Colorado	Recourse	**South Dakota**	Recourse
Georgia	Recourse	**Tennessee**	Recourse
Hawaii	Recourse	**Texas**	Recourse
Idaho	Recourse	**Utah**	Recourse
Iowa	Non-recourse	**Virginia**	Recourse
Michigan	Recourse	**Washington**	Non-recourse
Minnesota	Non-recourse	**Washington DC**	Recourse
Mississippi	Recourse	**West Virginia**	Recourse
Missouri	Recourse	**Wisconsin**	Non-recourse
Montana	Non-recourse	**Wyoming**	Recourse
Nevada	Recourse		

Notes: This table shows the classification of U.S. states into recourse and non-recourse markets according to Ghent and Kudlyak (2011).

Table 3. Variable definition

Variables	Description	Data Source
TT	Typical value for homes within the 65th to 95th percentile range ($)	Zillow
MT	Typical value for homes in the 35th to 65th percentile range ($)	Zillow
BT	Typical value for homes within the 5th to 35th percentile range ($)	Zillow
DR	The ratio of the number of loans in the foreclosure process over the total number of outstanding first lien loans (%)	CoreLogic
MortgageRate	30-Year Fixed Rate Mortgage Average in the United States (%)	Freddie Mac
Income	Per Capita Personal Income ($)	Bureau of Economic Analysis
Population	Census Bureau midyear population estimate (Number of Persons)	Bureau of Economic Analysis
Employment	Total Nonfarm Payroll (Thousands of Persons)	U.S. Bureau of Labor Statistics, Federal Reserve Bank of St. Louis
Permit	New Private Housing Units Authorized by Building Permits (Thousands of Units)	U.S. Census Bureau
INDPRO	Industrial Production Index (2017=100)	Board of Governors of the Federal Reserve System
PPIACO	Producer Price Index by All Commodities (1982=100)	U.S. Bureau of Labor Statistics
SP500	S&P 500 Index	S&P Dow Jones Indices LLC
UMCSENT	University of Michigan Consumer Sentiment (1966: Q1=100)	University of Michigan

Notes: This table reports the description and the data sources of the variables used in the empirical analysis.

Table 4. Descriptive statistics – Annual data

Variable	Panel A. Recourse States					Panel B. Non-Recourse States					Transformation
	N of Obs	Mean	SD	ADF test		N of Obs	Mean	SD	ADF test		
				Level	Transformed				Level	Transformed	
TT	2458	271740	121556	62.03	477***	1702	393650	251241	117.86	395***	1
MT	2458	156521	74440	55.50	459***	1702	235428	138155	157.23	386***	1
BT	2448	91207	52518	81.07	449***	1686	148110	91902	123.10	339***	1
DR	2800	0.820	0.690	66.76	487***	1920	0.900	0.873	56.59	360***	2
Income	2800	35713	9769	33.53	1364***	1920	37942	9987	11.18	921***	1
MortgageRate	2800	5.192	1.250	404***	-	1920	5.192	1.250	277***	-	3
Population	2800	592073	1080340	230.03	544***	1920	723180	1560305	194.81	322***	1
Employment	2800	271.58	522.18	246.01	847***	1920	316.57	699.18	149.41	532***	1
Permit	2800	4004	4641	116.12	374***	1920	4506	4043	97.30	243***	1
INDPRO	2800	96.45	4.77	53.09	1301***	1920	96.45	4.77	36.41	892***	1
PPIACO	2800	175.06	24.83	18.95	536***	1920	175.06	24.83	13.00	367***	1
SP500	2800	1618	627	0.98	2386***	1920	1618	627	0.67	1636***	1
UMCSENT	2800	85.79	11.41	101.19	803***	1920	85.79	11.42	69.39	551***	1

Notes: This table reports the descriptive statistics of all variables in the annual dataset. Column *ADF test* gives the value of the P-statistics from the ADF test for the original level data and the data after transformation. *** indicates the null hypothesis that all panels contain unit roots is rejected at 1% statistical levels according to the P-statistics and p-value from the ADF test. The last column, Transformation, indicates the transformation of the original data: 1= log difference, 2=difference, 3=no transformation.

Table 5. Descriptive statistics – Monthly data

Variable	Panel A. Recourse States					Panel B. Non-Recourse States					Transformation
	N of Obs	Mean	SD	ADF test		N of Obs	Mean	SD	ADF test		
				Level	Transformed				Level	Transformed	
TT	29273	268956	119662	120.88	761***	20282	389111	248072	110.52	384***	1
MT	29269	154474	72896	102.05	736***	20287	231960	135723	92.90	392***	1
BT	29166	89628	51133	66.56	876***	20095	145336	89720	74.83	466***	1
DR	33600	0.820	0.699	30.24	5940***	23040	0.900	0.884	15.84	2808***	2
Income	33600	36262	9912	213.10	962***	23040	38570	10280	69.43	580***	1
MortgageRate	33600	5.193	1.277	535***	-	23040	5.193	1.277	367***	-	3
Population	33600	595408	1087645	217.99	523***	23040	726478	1564406	178.13	273***	1
Employment	33600	271.58	522.11	98.59	5190***	23040	316.57	699.05	48.65	3326***	1
Permit	33599	4004	4678	206.94	10074***	23040	4506	4111	57.47	6920***	1
INDPRO	33600	96.45	4.92	289.68	1911***	23040	96.45	4.92	198.64	1311***	1
PPIACO	33600	175.40	26.16	154.91	4610***	23040	175.40	26.16	106.22	3161***	1
SP500	33600	1578	590	19.42	5310***	23040	1578	590	13.32	3641***	1
UMCSENT	33600	85.78	12.23	236.77	9965***	23040	85.78	12.23	162.36	6833***	1

Notes: This table reports the descriptive statistics of all variables in the monthly dataset. Column *ADF test* gives the value of the P-statistics from the ADF test for the original level data and the data after transformation. *** denote the null hypothesis that all panels contain unit roots is rejected at 1% statistical levels according to the P-statistics and p-value from the ADF test. The last column, Transformation, indicates the transformation of the original data: 1= log difference, 2=difference, 3=no transformation.

Table 6. Granger causality tests

	Panel A: ΔMT → ΔDR		Panel B: ΔDR → ΔMT	
	Recourse	**Non-recourse**	**Recourse**	**Non-recourse**
VAR	193.19***	6778.08***	883.83***	1471.21***
Panel VAR	3.16*	26.2***	5.11**	21.36***
Panel VECM (All controls)	7.41	11.88**	22.68***	40.29***
Panel VECM (no interpolated data)	6.78	11.57**	23.72***	38.63***

Notes: This table reports Granger causality tests for the interaction between house price returns and mortgage default risk. The 1st row shows the specific Granger causal relationship to be tested. The columns in *Panel A: ΔMT → ΔDR* report the test results for the null hypothesis that house price returns do not Granger-cause mortgage default. The columns in *Panel B: ΔDR → ΔMT* report the test results for the null hypothesis that mortgage default risk does not Granger-cause house price returns. ** and *** indicate that the null hypothesis is rejected at 5%, and 1% significance level, respectively.

Table 7. Forecast error variance decomposition

Horizons	% of variance of ΔDR explained by shock to ΔMT		% of variance of ΔMT explained by shock to ΔDR	
	Recourse	**Non-recourse**	**Recourse**	**Non-recourse**
Panel A. VAR (Simulated, 2 controls)				
2	0.26%	17.21%	3.89%	6.89%
4	1.19%	42.15%	7.24%	10.49%
6	1.19%	42.20%	7.26%	10.36%
8	1.19%	42.40%	7.37%	10.55%
10	1.21%	42.45%	7.40%	10.56%
Panel B. Panel VAR (Annual, All controls)				
2	1.83%	10.50%	2.05%	19.44%
4	2.31%	8.44%	2.69%	24.38%
6	2.37%	8.23%	2.77%	25.58%
8	2.37%	8.22%	2.78%	25.81%
10	2.37%	8.23%	2.78%	25.85%
Panel C. Panel VECM (Monthly, All controls)				
12	3.59%	7.68%	1.23%	5.71%
24	4.26%	9.90%	1.44%	7.04%
36	4.31%	10.37%	1.46%	7.26%
48	4.31%	10.48%	1.46%	7.31%
60	4.32%	10.51%	1.46%	7.32%
Panel D. Panel VECM (Monthly, without interpolated variables)				
12	3.75%	8.26%	1.30%	5.32%
24	4.48%	10.89%	1.52%	6.61%
36	4.54%	11.52%	1.54%	6.85%
48	4.54%	11.69%	1.54%	6.91%
60	4.54%	11.73%	1.54%	6.92%

Notes: This table reports the forecast error variance of the change in the mortgage default rate and the house price appreciation rate due to an innovation in the other variable. The 1st column reports the horizons of the forecast error variance decomposition. The 2nd and 3rd columns report the percentage of forecast error variance of ΔDR explained by ΔMT innovations in recourse and non-recourse states, respectively. The 4th and 5th columns report the percentage of forecast error variance of ΔMT explained by ΔDR innovations in recourse and non-recourse states, respectively.

Table 8. Cointegration tests

Test_Statistics	Time-demeaned without trend		Time-demeaned with trend	
	Recourse	Non-recourse	Recourse	Non-recourse
Panel v	-2.527**	-6.375***	1.595	-2.444**
Panel rho	3.102***	8.496***	1.349	5.836***
Panel t	2.801***	9.079***	1.519	5.936***
Panel ADF	3.503***	8.756***	1.942*	5.598***
Group rho	-.7027	6.039***	-1.752*	5.239***
Group t	-1.675*	5.643***	-1.838*	4.791***
Group ADF	-1.692*	3.666***	-1.778*	3.008***

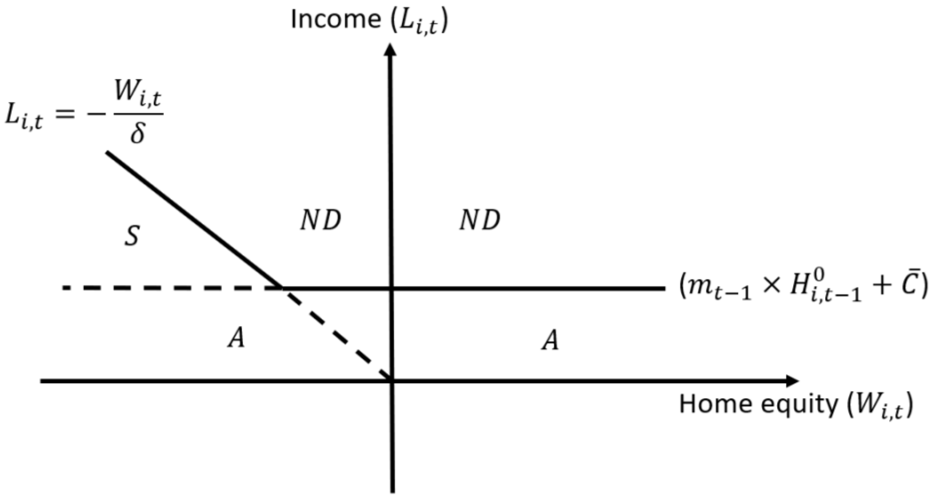
Notes: This table reports the results from Pedroni panel cointegration tests for the long-term relationship between house price tiers and mortgage default rates.

Table 9. Coefficients of Panel VECM and error correction terms

Variables	Recourse				Non-Recourse			
	ΔTT	ΔMT	ΔBT	ΔDR	ΔTT	ΔMT	ΔBT	ΔDR
$\alpha_{TT,t-1}$	1.214***	0.026	-0.011	0.002	1.250***	0.042	-0.032	0.011
	(0.025)	(0.028)	(0.033)	(0.006)	(0.043)	(0.039)	(0.044)	(0.010)
$\alpha_{TT,t-2}$	-0.229***	0.073*	0.055	-0.005	-0.382***	-0.047	0.031	-0.017
	(0.033)	(0.038)	(0.043)	(0.009)	(0.069)	(0.061)	(0.065)	(0.015)
$\alpha_{MT,t-1}$	0.085***	1.269***	0.097**	-0.008	0.050	1.231***	0.016	-0.024*
	(0.026)	(0.032)	(0.040)	(0.007)	(0.067)	(0.062)	(0.074)	(0.014)
$\alpha_{MT,t-2}$	-0.077**	-0.365***	-0.018	-0.004	0.150	-0.140	0.178*	0.021
	(0.036)	(0.044)	(0.054)	(0.011)	(0.100)	(0.092)	(0.099)	(0.021)
$\alpha_{BT,t-1}$	0.017	0.030*	1.247***	-0.009**	0.022	0.051	1.340***	-0.010
	(0.017)	(0.018)	(0.022)	(0.004)	(0.037)	(0.038)	(0.051)	(0.008)
$\alpha_{BT,t-2}$	-0.012	-0.015	-0.330***	0.014**	-0.098**	-0.129**	-0.512***	0.015
	(0.023)	(0.023)	(0.028)	(0.006)	(0.048)	(0.051)	(0.066)	(0.011)
$\alpha_{DR,t-1}$	-0.026	-0.022	-0.012	0.145***	-0.083**	-0.091**	-0.089**	0.358***
	(0.020)	(0.021)	(0.026)	(0.011)	(0.036)	(0.036)	(0.038)	(0.013)
$\alpha_{DR,t-2}$	-0.073***	-0.058***	-0.081***	0.050***	-0.083**	-0.086**	-0.088**	0.138***
	(0.019)	(0.021)	(0.026)	(0.010)	(0.037)	(0.037)	(0.040)	(0.015)
α_{ECT}	-0.011	-0.019**	-0.034***	-0.007	0.009	-0.002	-0.016	-0.009**
	(0.009)	(0.008)	(0.010)	(0.005)	(0.012)	(0.012)	(0.013)	(0.004)
β_{TT}	-0.508***	-0.508***	-0.508***	-0.508***	-0.524***	-0.524***	-0.524***	-0.524***
	(0.091)	(0.091)	(0.091)	(0.091)	(0.193)	(0.193)	(0.193)	(0.193)
β_{MT}	1.046***	1.046***	1.046***	1.046***	-1.246***	-1.246***	-1.246***	-1.246***
	(0.122)	(0.122)	(0.122)	(0.122)	(0.262)	(0.262)	(0.262)	(0.262)
β_{BT}	0.556***	0.556***	0.556***	0.556***	3.462***	3.462***	3.462***	3.462***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.122)	(0.122)	(0.122)	(0.122)
N of Obs	27,883	27,883	27,883	27,883	19,261	19,261	19,261	19,261

Notes: This table reports the estimation results of the Panel VECM with monthly data and all control variables as specified in Section 4.2.1. The regression equation includes five lags as determined by the Bayesian information criterion. For brevity, only the coefficients of the 1^{st} and 2^{nd} lags of the endogenous variables, the coefficients of the cointegrating relationship, and the coefficients of the error correction term are reported in the table.

Figure 1. Home equity, labor income and affordabiliy and strategic defaults



Notes: A=area of affordability default; S=area of strategic default; ND=area of non-default.

Figure 2. Simulated house prices in the recourse and the non-recourse market

This figure shows the simulation results of the equilibrium path of house prices in recourse and non-recourse markets over the first 30 periods.

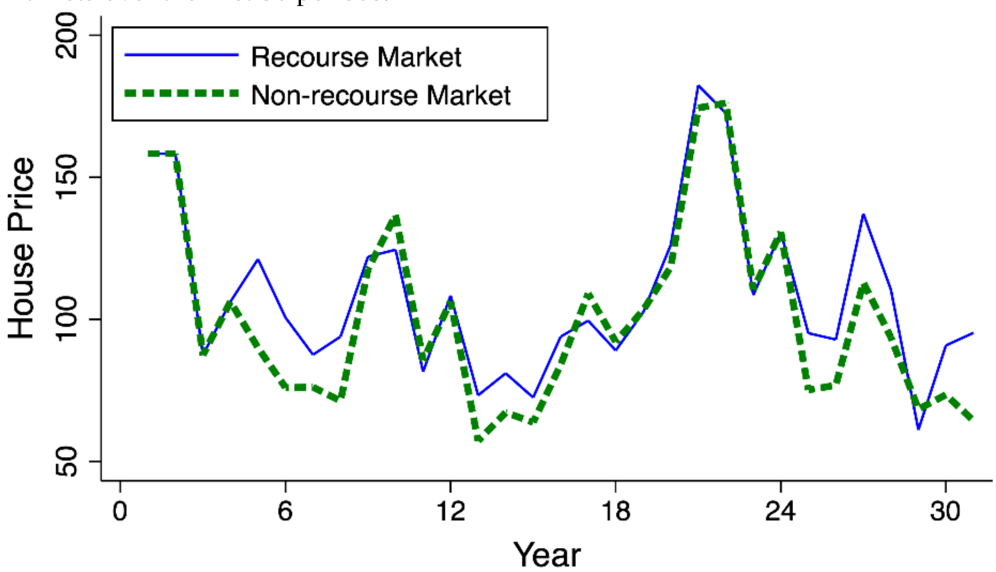


Figure 3. Location of metropolication statsisistica areas and states

This figure represents the locations of the metropolitan statistical areas (MSAs) and the states included in the sample of this study. Recourse states are coloured in dark blue and non-recourse states are coloured in light blue. The red dots represent locations of MSAs. MSAs from Hawaii are also included in our sample, but not shown in the figure.

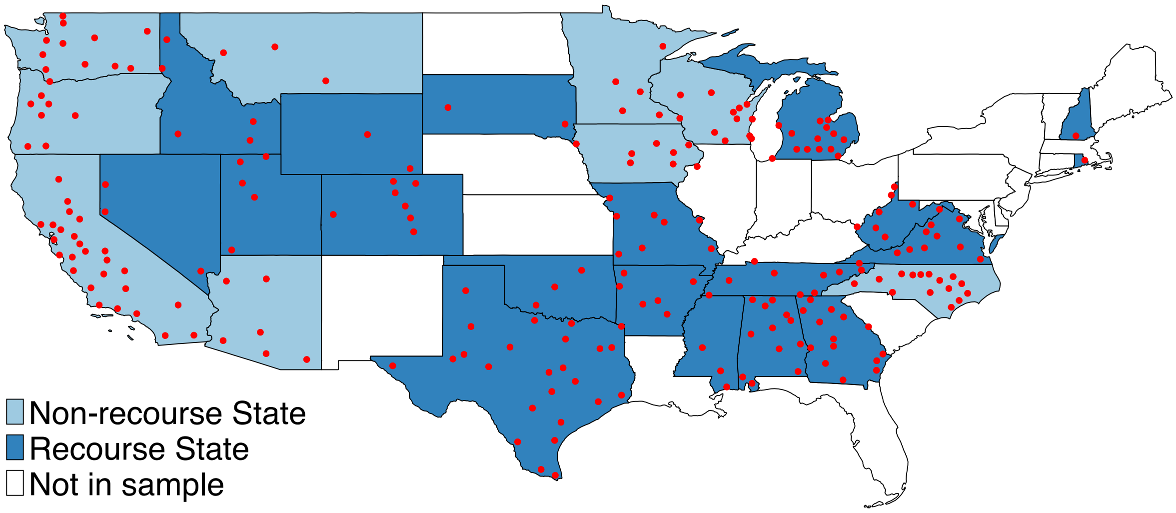


Figure 4. Middle-tier house price and average default rate in the US

This figure shows the monthly dynamics of middle-tier house prices and average default rates across MSAs within the sample period. The black solid line represents the middle-tier house price (MT) in the US, while the red dash line represents default rate (DR) in the US. The black bars represent the monthly return of middle-tier house price. The left axis shows the range of house prices, and the right axis shows the range of the default rate. The measurement unit of the left axis is 1,000 US dollars.

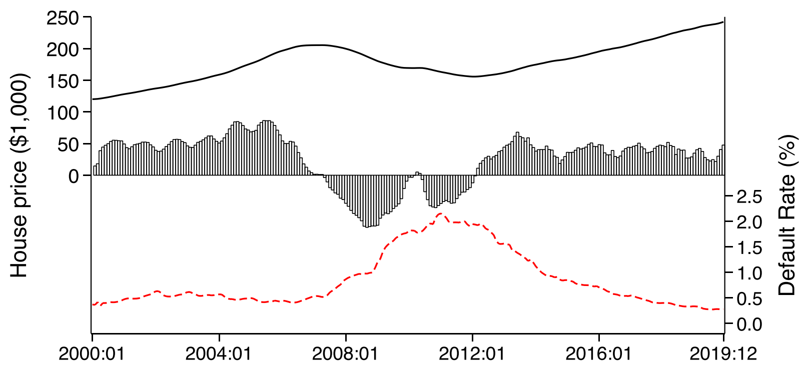
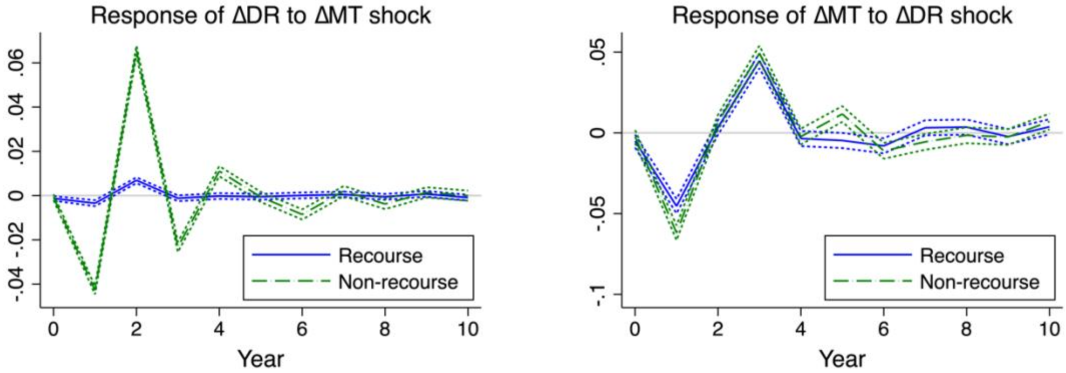


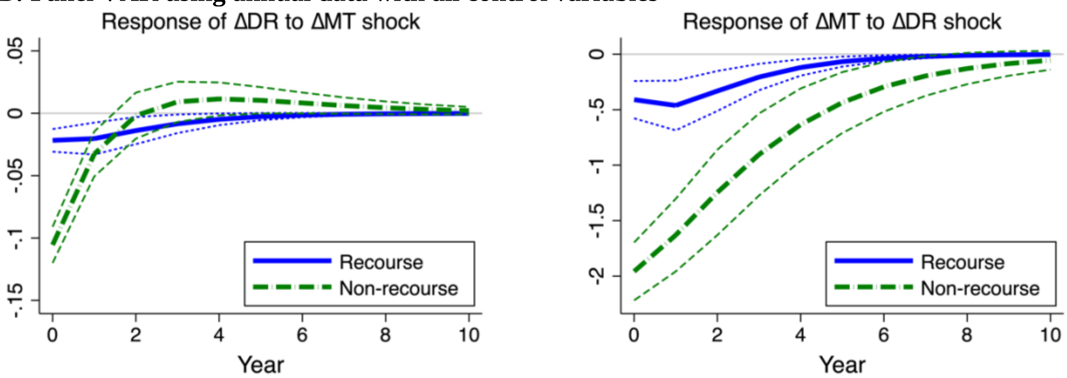
Figure 5. Impulse responses

The long-dash dot lines and thick solid lines represent the generalized impulse responses of mortgage default to a one standard deviation shock to house price returns and the response of house price returns to a one standard deviation shock to mortgage default in the forecasting periods after the shock. The dash lines represent the 95% confidence interval around the responses. Panels A, B, C and D represent the responses in different regressions.

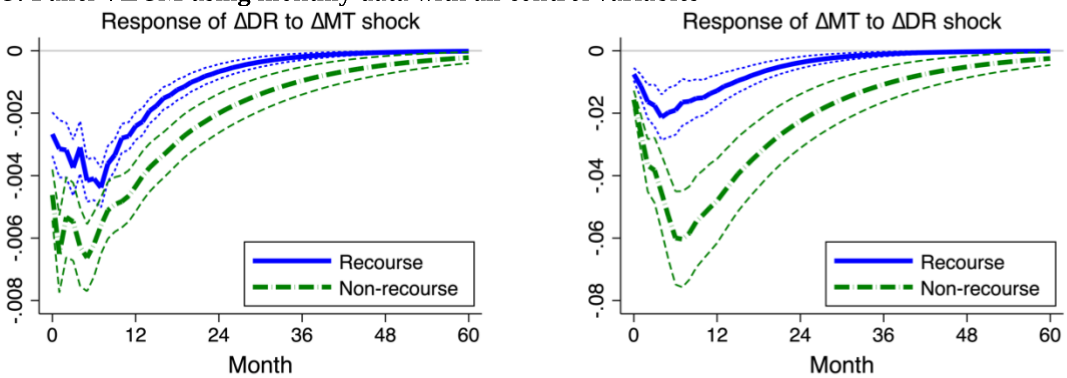
Panel A: VAR using simulated data



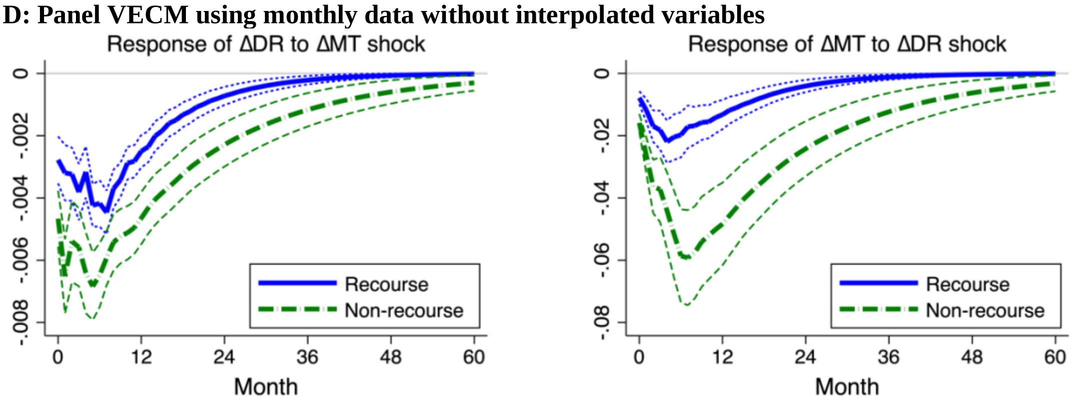
Panel B: Panel VAR using annual data with all control variables



Panel C: Panel VECM using monthly data with all control variables



Panel D: Panel VECM using monthly data without interpolated variables



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