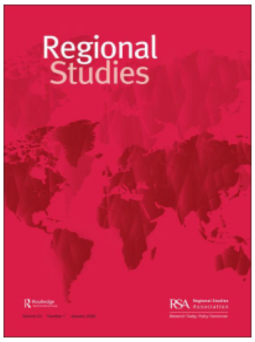

Regional Studies

ISSN: 0034-3404 (Print) 1360-0591 (Online) Journal homepage: www.tandfonline.com/journals/cres20

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To cite this article: Damian S. Damianov, Xiangdong Wang & Cheng Yan (2025) House price dynamics and mortgage defaults: the role of recourse, Regional Studies, 59:1, 2549592, DOI: 10.1080/00343404.2025.2549592

To link to this article: https://doi.org/10.1080/00343404.2025.2549592

REGIONAL STUDIES
2025, VOL. 59, NO. 1, 2549592
https://doi.org/10.1080/00343404.2025.2549592

House price dynamics and mortgage defaults: the role of recourse

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ABSTRACT
This paper investigates the relationship between house prices and mortgage defaults in recourse and non-recourse US metropolitan areas. The theoretical analysis shows that shocks to house price returns have a stronger effect on defaults in non-recourse markets than in recourse markets due to strategic default behaviour. Empirical evidence from a panel vector autoregressive (Panel VAR) model supports this prediction and, in addition, reveals a stronger house price response to defaults in non-recourse markets than predicted by the theoretical model. The findings highlight key differences in mortgage default dynamics across recourse and non-recourse markets, offering insights for households, lenders, policymakers and regulators.

KEYWORDS
Mortgage default; strategic default; recourse; house price dynamics

JEL D12, D14, E51, G21, G33, R31
HISTORY Received 2 September 2022; in revised form 30 July 2025

1. INTRODUCTION

The Global Financial Crisis has illustrated the central role mortgage lending plays in shaping household default behaviour. Its effects rippled across housing markets and financial institutions with profound and lasting consequences for the broader economy.

A growing body of research shows that mortgage recourse provisions – whether lenders can pursue borrowers for outstanding debt beyond the property sale price – significantly influence the likelihood of default. In the absence of mortgage recourse, borrowers may choose to default not due to financial distress but because their mortgage debt exceeds the current market value of their home.

Empirical evidence indicates that when lenders cannot hold borrowers accountable for outstanding debt, the default risk increases. Ghent and Kudlyak (2011) found that borrowers with negative equity are 1.32 times more likely to default when recourse is not an option. Similarly, Gerardi et al. (2018) emphasised the significance of strategic considerations in default decisions, revealing that over 38% of borrowers who default could still make payments without reducing their consumption.

These findings point to the critical role of mortgage contract design in shaping borrowers' default behaviour. They also suggest that recourse and non-recourse markets exhibit different price dynamics due to different foreclosure rates. Yet, house price dynamics have rarely been studied through the lens of mortgage recourse. In this article, we aim to address this gap by explicitly focusing on the interdependence between foreclosures and house price dynamics in recourse versus non-recourse markets.

The connection between foreclosures and house prices carries significant policy implications and has been explored in the literature on how public policy should respond to the financial crisis. Calomiris et al. (2013) estimated a panel vector-autoregressive model of US states and demonstrate that while foreclosures adversely affect house prices, the reverse impact is even more pronounced. Therefore, policy measures for the crisis should focus on stabilising house prices. While some borrowers in these local markets default for strategic reasons, Calomiris et al. (2013) did not consider the role of recourse. Thus, there remains a void in our understanding of how house prices interact with defaults and the role of recourse in shaping this interaction.

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/00343404.2025.2549592

The aim of this article is to shed light on this very question. It develops an overlapping generations model that integrates affordability and strategic default considerations. In the model, successive cohorts of home buyers enter the housing market, purchase homes and subsequently decide whether to default based on the income shock they experience and the recourse provisions of their mortgage contracts. House prices are determined in market equilibrium such that, in each period, foreclosed properties and homes vacated by exiting households are purchased by a new cohort of buyers, so that the housing market clears.

In a recourse market, households default only for affordability reasons, i.e., when their income is insufficient to make their mortgage payments and afford a minimum level of non-housing consumption. In a non-recourse market, households which are in negative equity default also for 'strategic' reasons.

The model illustrates that after a negative house price shock in the non-recourse market, house prices are more likely to fall further when the foreclosed homes of strategic defaulters are sold. For this reason, non-recourse markets experience deeper downturns. However, house prices in both recourse and non-recourse markets recover as fundamentals improve. In the long run, house prices primarily reflect the state of fundamentals, such as household income and interest rates.

Monte Carlo simulations are conducted to provide deeper insights into the interaction between house prices and default rates. They illustrate that the change in the default rate in the non-recourse market is more sensitive to house price return shocks relative to 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 pronounced.

These theoretical predictions are studied empirically using a large set of US metropolitan statistical areas (MSAs) in recourse and non-recourse states. A panel vector-autoregressive (Panel VAR) model in annual frequency is estimated for the 2000–2019 period for the recourse and non-recourse sub-samples of MSAs. In line with the theoretical framework, the appreciation rate of house prices and the change in the mortgage default rate at the MSA level are treated as endogenous variables while the per capita personal income of households and the 30-year mortgage rate are treated as exogenous. The empirical specification also includes other widely used determinants of demand and supply of housing such as population, employment, building permits, the industrial production index, the producer price index, the Standard and Poor (S&P) 500 index, as well as household sentiment.

The empirical results largely align with the theoretical predictions and support the described theoretical mechanisms. 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 first year following the shock. However, the response of house price returns to changes in the default rate is stronger in the non-recourse market than predicted by the theoretical model. One potential explanation for this effect is that after an increase in the mortgage default rate, households anticipate more defaults in non-recourse markets where some households default for strategic reasons.

While the analysis presented here, as most literature, is motivated by the subprime mortgage crisis, the results also carry implications for current economic and housing market conditions. The theoretical framework illustrates how house price returns respond to shocks 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, the analysis spans an entire housing market cycle. In that respect, the empirical results have validity beyond the crisis period.

The remainder of this paper is organised as follows: Section 2 reviews the literature on the interaction between house prices and default risk. Section 3 introduces the theoretical model and Section 4 describes the data and methodology. Section 5 presents the empirical results and Section 6 concludes.

2. RELATED LITERATURE

Since the subprime mortgage crisis, extensive research has examined the factors influencing mortgage defaults and their interaction with house prices. Two strands of literature have developed, focusing either on individual household behaviour (micro-level studies) or equilibrium market dynamics using aggregated regional or national data (macro-level studies). The former strand of literature is more established, while the latter is still nascent. This article seeks to advance the latter strand of literature on the dynamic interdependence between house prices and mortgage defaults.

2.1. Micro-level studies

Studies using household-level data typically examine one direction of causality: either the impact of house prices on mortgage defaults or the reverse effect of mortgage defaults on house prices. These studies employ identification strategies that allow for a causal interpretation of the observed effects. They analyse individual loan performance by considering borrower characteristics, loan attributes and local economic and demographic conditions.

2.1.1. The impact of house prices on mortgage defaults

Adverse house price shocks affect mortgage defaults due to strategic default behaviour of some borrowers and spillover effects among borrowers. Strategic default occurs when households default despite their ability to pay, typically due to negative equity (Bradley et al., 2015; Mian & Sufi, 2009). Strategic defaults are also referred to as option-theoretic defaults because their financial outcomes mirror those of exercising an American put option, with the exercise price corresponding to the remaining mortgage balance. Foster and Van Order (1984) provide critical values for negative equity below which mortgage default is optimal.

Gerardi et al. (2018) introduced a novel method for identifying strategic defaults by constructing household budget sets. Their approach determines which borrowers can sustain mortgage payments without reducing consumption and finds that 38% of defaults in the Panel Study of Income Dynamics are strategic. Additional research on strategic default and the effect of social contagion includes contributions from Guiso et al. (2013), Mayer et al. (2014), Bradley et al. (2015) and Goodstein et al. (2017).

Some studies explicitly focus on the impact of lender recourse on default behaviour. Ambrose et al. (1997) found that recourse reduces default rates by allowing lenders to pursue borrowers' other assets. Ghent and Kudlyak (2011) demonstrated that negative equity borrowers in non-recourse states are more likely to default, with the effect being stronger for more expensive homes. Overall, evidence supports strategic default behaviour, though its estimated magnitude varies, with declines in home values serving as a primary driver of defaults, further intensified by local spillover effects.

2.1.2. The impact of mortgage defaults on house prices

Mortgage defaults negatively affect house prices by increasing the number of homes for sale due to foreclosures and creating adverse spillover effects on communities. Campbell et al. (2011) estimated a foreclosure discount of up to 27% due to potential home damage and lenders' urgency to sell. Mian et al. (2015) utilised state judicial requirements to address endogeneity and found that foreclosures accounted for 33% of the house price decline from 2007 to 2009.

Foreclosures also impose negative externalities on neighbouring properties. Lin et al. (2009) estimated price declines of 8.7% for properties within 100 metres and 4.7% within 200 metres of a foreclosure. Campbell et al. (2011) found that forced sales lead to neighbourhood price discounts of 3% to 7%. Studies by Harding et al. (2009) highlighted a contagion effect due to neglected foreclosed properties, while Hartley (2014) identified supply as the primary factor affecting prices. Anenberg and Kung (2014) showed that disamenity effects are more relevant in high-density, low-price neighbourhoods. Given the strong correlation between house prices in regional and national markets, these findings have significant implications for financial market stability and the broader economy (Bissoondeeal, 2021; Tsai, 2015).

2.2. Macro-level studies

A growing body of literature explores the relationship between house prices, mortgage leverage and defaults through macroeconomic dynamic equilibrium frameworks. Guren and McQuade (2020) showed that defaults weaken lenders' balance sheets, particularly when foreclosed properties are sold at a discount, resulting in credit rationing and reduced housing demand. Similarly, Chatterjee and Eyigungor (2015) demonstrated that in a non-recourse market, households in negative equity default and transition to the rental market, setting off a downward spiral in house prices – a cycle that government interventions, such as the 2009 Home Affordable Modification Program, can help mitigate.

Gete and Zecchetto (2024) expanded this analysis by comparing recourse and non-recourse regimes across Spain and the US Their national-level model, which endogenises interest rates, labour income and unemployment, found that the US (mainly non-recourse market) experienced a shorter recession and faster recovery than Spain (mainly recourse market). In their framework, household debt reduces non-housing consumption, but as economies recover from shocks, increased consumption in the non-recourse economy helps mitigate house price declines. Complementing these findings, Calomiris et al. (2013) provided evidence that house prices have a stronger influence on foreclosure rates than the reverse, suggesting the significance of strategic decisions made by homeowners and lenders. Building on this literature, this article examines the role of recourse in the relationship between house prices and defaults across US metropolitan areas.

3. MODEL

This section presents an equilibrium model of the dynamic relationship between house prices and mortgage defaults in recourse and non-recourse markets. The framework incorporates key elements from Campbell and Cocco (2015) regarding household preferences and the calibration of parameters but differs in that house prices are determined endogenously in the model rather than being specified by an exogenous stochastic process. In recourse markets, defaults occur due to affordability issues, whereas in non-recourse markets, strategic defaults might also arise. The analysis is focused on the way these differences affect foreclosure rates and shape equilibrium house price dynamics under the two mortgage systems.

3.1. Timing

Time is discrete, measured in years and indexed by t. Households make decisions over four periods.[1] In each period t a new generation (of age $a = 0$) of N homebuyers enter the housing market. They decide on the sizes of the homes they buy, and their non-housing consumption given their realised income in that period. In the next period, when of age $a = 1$ households experience another income shock and decide whether to default on their mortgage. Defaulting homeowners leave the market at age $a = 2$ and their homes are sold to a newly arriving cohort of buyers. Non-defaulting homeowners occupy their homes for another two years (when of age $a = 2$ and $a = 3$) and leave the market for exogenous reasons in the following period (when of age $a = 4$). A newly arriving cohort of buyers buys their homes, along with the homes lost in foreclosures.

3.2. Income

Each home buyer i of age $a = 0$ receives a stochastic labour income $L^0_{i,t}$ which is governed by the process,

$$Log(L^0_{i,t}) = Log(L^0_{i,t-1}) + \nu_t + \epsilon^0_{i,t}, \quad (1)$$

where ν_t is a permanent income shock affecting all home buyers in the period t and $\epsilon^0_{i,t}$ is an i.i.d. normally distributed idiosyncratic shock with a mean of zero and a variance of σ^2_ϵ affecting only the buyer i. The permanent shock is assumed to follow a random walk,

$$\nu_t = \nu_{t-1} + \eta_t, \quad (2)$$

where ν_t has a mean of g and η_t is normally distributed with a mean of zero and a variance of σ^2_η.

3.3. Interest rates

Each household can borrow at an interest rate of r_t which follows an AR (1) process considered by Campbell and Cocco (2015) and given by,

$$\mathrm{r_t} = \mu(1-\varphi) + \varphi \mathrm{r_{t-1}} + u_t, \quad (3)$$

where $\mathrm{r_t} = log(1 + R_t)$ is the log interest rate in period t, μ and φ are calibrated parameters and u_t is a normally distributed shock with a mean of zero and a variance of σ^2_u. A fixed-rate mortgage is considered with a full amortisation over a period of T years.[2] That is, for each \$1 borrowed, the household repays,

$$m(r_t,\ T) = r_t \times \frac{(1+r_t)^T}{(1+r_t)^T - 1} \quad (4)$$

per year.

3.4. Household preferences and decisions

Household i of age $a = 0$ buys a home of size denoted by $H^0_{i,t}$ and spends $C^0_{i,t}$ on non-housing consumption. A unit of housing in that period can be purchased for the price of P_t (to be determined in equilibrium). Following Campbell and Cocco (2015), each homebuyer i has a utility function given by,

$$U(H^0_{i,t}, C^0_{i,t}) = \theta \frac{{H^0_{i,t}}^{1-\gamma}}{1-\gamma} + \frac{{C^0_{i,t}}^{1-\gamma}}{1-\gamma}, \quad (5)$$

where θ measures the importance of housing relative to non-housing consumption and γ is the coefficient of relative risk aversion. The household makes a downpayment of $\omega P_t H^0_{i,t}$ (using existing savings) and borrows $(1-\omega)P_t H^0_{i,t}$ to purchase the home, where the downpayment to house price ratio ω is exogenously given. For convenience, we denote the per period repayment cost of a unit consumption of housing by,

$$m_t = m(r_t,\ T)(1-\omega)P_t. \quad (6)$$

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

$$m_t H^0_{i,t} + C^0_{i,t} \le L^0_{i,t}, \quad (7)$$

where $L^0_{i,t}$ is the household's labour income. With these preferences and budget constraint, the optimal home size is given by,[3]

$$H^{0*}_{i,t} = \left(\frac{\theta}{m_t}\right)^{\frac{1}{\gamma}} \times \frac{L^0_{i,t}}{\left(\frac{\theta}{m_t^{1-\gamma}}\right)^{\frac{1}{\gamma}} + 1}. \quad (8)$$

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

$$Log(L^1_{i,t+1}) = Log(L^0_{i,t}) + \nu_{t+1} + \epsilon^1_{i,t+1}. \quad (9)$$

Homeowners' default decisions depend on the realisations of income $L^1_{i,t+1}$, and house price P_{t+1}.[4]

3.4. Defaults

The decision to default depends on mortgage recourse.

3.4.1. Recourse mortgages

In a recourse mortgage contract, the lender can collect any remaining mortgage debt from the borrower, preventing strategic defaults. Defaults occur when shocks to labour income make it impossible for households to afford both their mortgage payments and their essential non-housing expenses. Household i of age $a = 1$ is in default when the following affordability condition is violated,

$$L^1_{i,t+1} - m_t H^0_{i,t} - \bar{C} \ge 0, \quad (A)$$

where $L^1_{i,t+1}$ denotes labour income, $m_t H^0_{i,t}$ the mortgage payment, and $\bar{C}$ the non-housing subsistence level.

3.4.2. Non-recourse mortgages

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

$$W^1_{i,t+1} = P_{t+1} H^0_{i,t} - (1-\omega) P_t H^0_{i,t} (1 + r_t - m_t), \quad (10)$$

where the first term is the value of the house in the 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 and 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 does not default strategically when,

$$W^0_{i,t+1} \ge -\delta L^1_{i,t+1}, \quad (S)$$

where $\delta > 0$ is the strategic default parameter. The parameter δ can be interpreted as a critical value of years of labour income that triggers strategic default. For example, $\delta = 1$ means that the household opts for strategic default as soon as its loss from purchasing the house exceeds the equivalent of one year's labour income. Household i of age $a = 1$ consumes $H^1_{i,t+1} = H^{0*}_{i,t}$ when the household is not in default (both (A) and (S) hold) and zero when the household has defaulted.

3.5. Housing market equilibrium

The housing stock is inelastic and normalised to $S = 1$, and in each period four cohorts of households (of ages $a = 0, 1, 2$ and 3) coexist in the housing market and occupy this stock. The price of a unit of housing P_t is determined in a partial market equilibrium in which aggregate demand corresponds to the housing stock, $D(P_t) = S$.[5] Aggregate demand is composed of the demand of the four cohorts,

$$D(P_t) = H^0_t(P_t) + H^1_t(P_{t-1}) + H^2_t(P_{t-1}, P_{t-2}) + H^3_t(P_{t-2}, P_{t-3}) \quad (11)$$

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

$$H^0_t(P_t) = \sum_{i=1}^{N} H^{0*}_{it}(L_{it}, P_t), \quad (12)$$

where H^{0*}_{it} is given by Equation (8). Cohort $a = 1$ of households have purchased their homes in the previous period and their demand is given by,

$$H^1_t(P_t) = \sum_{i=1}^{N} H^{0*}_{i,t-1}(L_{i,t-1}, P_{t-1}) \quad (13)$$

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

$$H^2_t(P_t) = \sum_{i=1}^{N} H^{0*}_{i,t-2}(L_{i,t-2}, P_{t-2}) \times ND(L_{i,t-1}, P_{t-1}, P_{t-2}), \quad (14)$$

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.

3.6. Model predictions

For the analysis, it is helpful to denote the area of affordability default as (AD) and strategic default as (SD) in the home equity-income graph (W, L) as illustrated in Figure 1.

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. Assume a sufficiently strong downward movement of home values so that house prices have declined, $P_{t-1} < P_{t-2}$ and home equity has turned negative, $W^1_{i,t-1} < 0$. For a given home equity level $W^1_{i,t-1}$, the probability of default in a non-recourse market is given by the probability that the realisation of income would be either in area AD or in area SD. In a recourse market, default occurs only when the income realisation is in area AD. 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. It needs to be shown that if $P_{t-1} < P_{t-2}$ and $W^1_{i,t-1} < 0$, the next period price in a non-recourse market would be lower: $P^{NR}_t \leq P^R_t$. As in a non-recourse market some buyers of age $a = 2$ are strategic defaulters, there

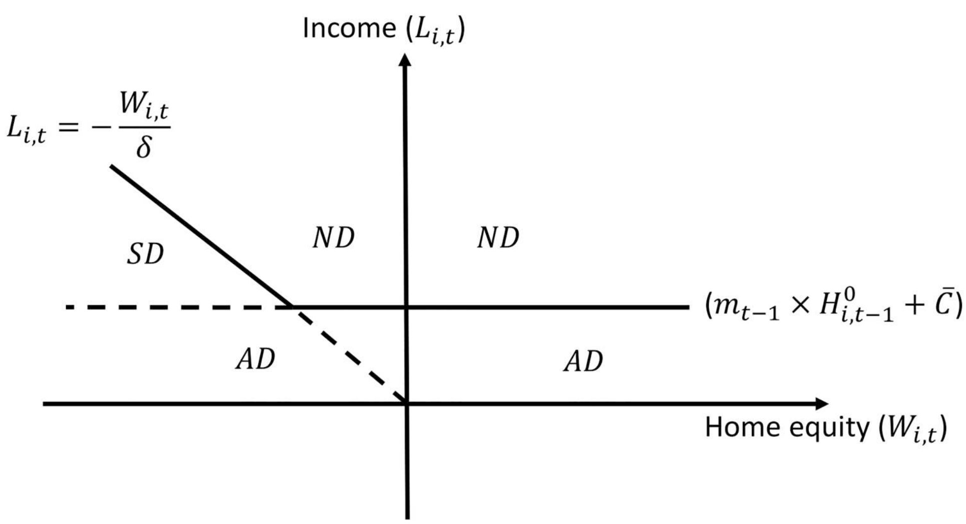

Figure 1. Home equity, labour income and areas of default.
Notes: AD = area of affordability default; SD = area of strategic default; ND = area of non-default.
Source: Authors' own illustration.

are fewer defaults in the recourse market:

$$ND^R(L_{i,t-1}, P_{t-1}, P_{t-2}) \geq ND^{NR}(L_{i,t-1}, P_{t-1}, P_{t-2}). \quad (15)$$

As more homeowners of age $a = 2$ are still in their homes in the recourse market, that is, $H_t^{2,R}(P_t) \geq H_t^{2,NR}(P_t)$, it follows that $D^R(P_t) \geq DN^R(P_t)$ and hence $P_t^{NR} \leq P_t^R$.

3.7. Monte-Carlo simulation

Further insights into the model predictions can be obtained from simulating the price formation and the default processes in the recourse and non-recourse market. A Monte-Carlo simulation is performed for 10, 000 periods and $N = 5$ groups of buyers entering the market each period. Households are assumed to default for affordability reasons when they cannot afford the subsistence non-housing consumption level of $\bar{C} = 0.1$ while also making their mortgage payment. Households default strategically when their negative equity exceeds their annual labour income (i.e., the default parameter is $\delta = 1$). The loan-to-value ratio is set at 95% (i.e., $\omega = 0.05$),[6] while the remaining parameters of the model are set to the values calibrated by Campbell and Cocco (2015) as shown in Table 1.

The model is initialised by assuming that there are no defaults in the first four periods. The household income in the initial periods is set to $L_{i,t}^0 = 1$ 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,

$$P_1 = P_2 = \frac{4N\theta}{(1-\omega)m_1} = 158.33. \quad (16)$$

For all subsequent periods, house prices and default rates are determined endogenously and depend on the realisation of the stochastic labour income and the interest rate processes as specified in Equations (1), (2) and (3). An example of the equilibrium path of house prices for 30 periods is presented in Figure 2.

The figure visualises several key properties. First, long-term house prices in recourse and non-recourse markets 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, differ across the recourse and the non-recourse market. Assuming a negative shock to fundamental variables leads to a decline in home values, this initial drop triggers more defaults in non-recourse markets. These defaults, in turn, amplify the decline in home values in the subsequent period. 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 available homes 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, prices in the non-recourse market might even temporarily exceed prices in the recourse market.

Table 1. Calibration of parameters.

Parameter	Value	Interpretation	Source
Household preferences			
θ	0.3	Importance of housing consumption	Campbell and Cocco (2015)
Y	2.0	Coefficient of relative risk aversion	Campbell and Cocco (2015)
Labour income			
g	0.080	Mean log real income growth	Campbell and Cocco (2015)
σ_η	0.063	St. dev. of permanent income shock	Campbell and Cocco (2015)
σ_ε	0.225	St. dev. of idiosyncratic transitory income shock	Campbell and Cocco (2015)
Interest rate			
μ	0.012	Mean value of the AR (1) process	Campbell and Cocco (2015)
φ	0.825	Autoregressive term	Campbell and Cocco (2015)
σ_ε	0.009	St. dev. of interest rate shock	Campbell and Cocco (2015)
Downpayment			
ω	0.05	Downpayment as a percentage of home value	Zillow (2024)
Mortgage repayment period			
T	30	Years of repayment with full amortisation	Kish (2022)

Notes: This table reports the calibrated parameters used in the overlapping generations model.

Using the data generated from the Monte-Carlo simulation, we estimate the following vector autoregressive (VAR) model, a panel version of which will also be estimated with actual data from MSAs.

$$\Delta \boldsymbol{Y}_t = \begin{pmatrix} \Delta HP_t \\ \Delta DR_t \end{pmatrix} = \sum_{j=1}^{p} \boldsymbol{A}_j \cdot \pm \Delta \boldsymbol{Y}_{t-j} + \boldsymbol{B} \cdot \boldsymbol{X}_t + \boldsymbol{\varepsilon}_t, \quad (17)$$

where the endogenous variables are the house price appreciation rate, $\Delta HP_t = Log(P_t) - Log(P_{t-1})$, and the change in the default rate $\Delta DR_t = DR_t - DR_{t-1}$. The

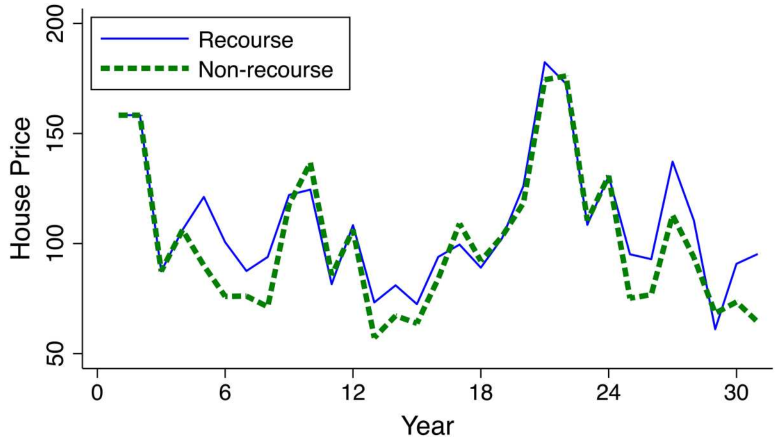

Figure 2. Simulated house prices in the recourse and the non-recourse market.
Notes: Simulated equilibrium path of house prices in recourse and non-recourse markets over the first 30 periods.
Source: Authors' own illustration.

vector of exogenous (or fundamental) variables $\boldsymbol{X}_t = \begin{bmatrix} \nu_t \\ r_t \end{bmatrix}$ includes the income shock ν_t and the realised interest rate r_t. Furthermore, $\boldsymbol{A}_j$ 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 presented in Section 5 alongside the empirical results for comparison purposes. The VAR system using the simulated data is estimated with twenty-four lags ($p = 24$), which is the optimal number of lags determined by the Bayesian information criterion.[7]

4. DATA, METHODOLOGY AND DESCRIPTIVE STATISTICS

The data sample covers 236 MSAs across 31 US states from 2000 to 2019. States are classified as recourse or non-recourse according to Ghent and Kudlyak (2011). This classification is based on how easily lenders can obtain a deficiency judgment when foreclosure sales do not cover the outstanding mortgage balance. To measure the impact of recourse on default risk, the analysis focuses on non-judicial states where foreclosure does not require a court order, and lenders can foreclose using the power of sale clause in the mortgage contract.[8] This approach allows default risk to be attributed to the recourse regime rather than differences in foreclosure procedures. Table 2 presents the state classifications and Figure 3 depicts the geographical locations of the states and MSAs.

The final sample has 140 MSAs from recourse states and 96 MSAs from non-recourse states. The variables used in this study include Zillow's middle-tier house price indices, CoreLogic's mortgage default rates and additional macroeconomic and demographic controls collected from multiple sources.

4.1. House prices

Zillow's middle-tier house price indices (HP) measure the annual appreciation of a typical home in each Metro region.[9] Since January 2023, these tiered indices have been produced by Zillow using its 'neural Zestimate', which provides a regularly updated property value estimate regardless of whether there is an underlying transaction on the property or not. This estimate is generated by a machine learning algorithm in which neural networks are employed and trained on historical property data, including sales transactions, tax assessments, public records and home-specific details such as square footage and location. Annual appreciation is calculated as the difference in each year's logarithms of the December price indices.

Table 2. Classification of states.

States	Recourse/ Non-recourse	States	Recourse/ Non-recourse
Alabama	Recourse	Nevada	Recourse
Alaska	Non-recourse	New Hampshire	Recourse
Arizona	Non-recourse	North Carolina	Non-recourse
Arkansas	Recourse	Oklahoma	Recourse
California	Non-recourse	Oregon	Non-recourse
Colorado	Recourse	Rhode Island	Recourse
DC	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	West Virginia	Recourse
Mississippi	Recourse	Wisconsin	Non-recourse
Missouri	Recourse	Wyoming	Recourse
Montana	Non-recourse		

Notes: This table shows the classification of non-judicial US states in the data sample as recourse and non-recourse markets, based on Ghent and Kudlyak (2011).

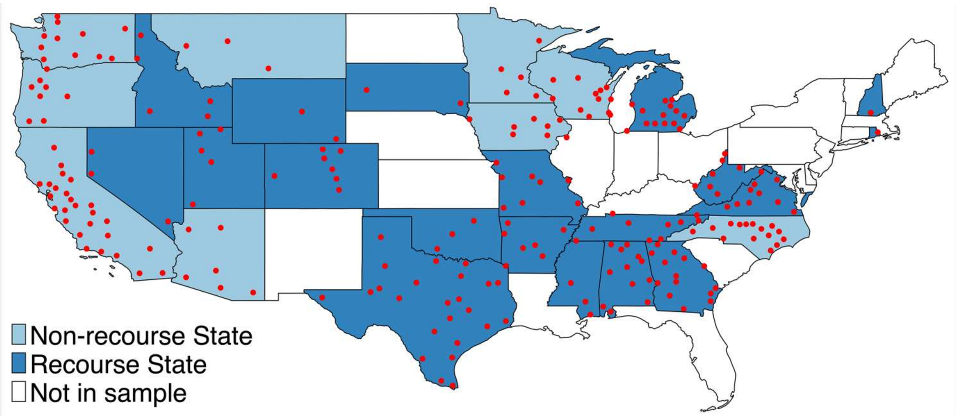

Figure 3. Map of US metropolitan statistical areas and states.
Notes: Metropolitan statistical areas (MSAs) and states included in the data sample. Recourse states are shaded in dark blue, while non-recourse states in light blue. Red dots indicate the locations of MSAs. MSAs from Hawaii are included in the sample but not shown in the map.
Source: 2021 US state boundary data from the US Census Cartographic Boundary Files.

4.2. Default rates

The mortgage default risk (DR) is measured by the proportion of loans in foreclosure compared to the total number of outstanding first lien loans. Foreclosure refers to the legal procedure by which an owner's property rights are terminated, usually because of default. Data are sourced from the MarketTrends dataset for each core-based statistical areas, which is provided monthly by CoreLogic Servicing and Securities products. This dataset covers approximately 85% of loans and associated foreclosures in the market. The monthly average is taken to calculate annual values for the proportion of loans in foreclosure. The dynamics of the house price and the default rates (averaged across MSAs) are presented in Figure 4.

4.3. Macroeconomic and demographic control variables

The empirical specification includes macroeconomic and demographic factors to account for their effect on the demand and supply of homes. In line with the theoretical model, the empirical specification includes the per capita personal income (INC) at the MSA level and the 30-year mortgage rate (MTGR). The former variable is obtained from the Bureau of Economic Analysis (www.bea.gov), and the latter from FRED (https://fred.stlouisfed.org/) at a weekly frequency and averaged over all weeks in each year to derive the annual rate. The other control variables included in the model are employment (EMP), building permits (PERM), industrial production index (INDP) and the S&P 500 index (SP500), following the approach of Bork et al. (2020). To capture household sentiment, the University of Michigan's Consumer Sentiment Index (SENT) is also included, consistent with the methodology of De Stefani (2021). Additionally, population (POP) is incorporated as a control variable in accordance with He and Wen (2017). Finally, the Producer Price Index for all commodities (PPI) is included to account for supply-side cost effects on house prices. The definitions and data sources for these variables are presented in Table 3.

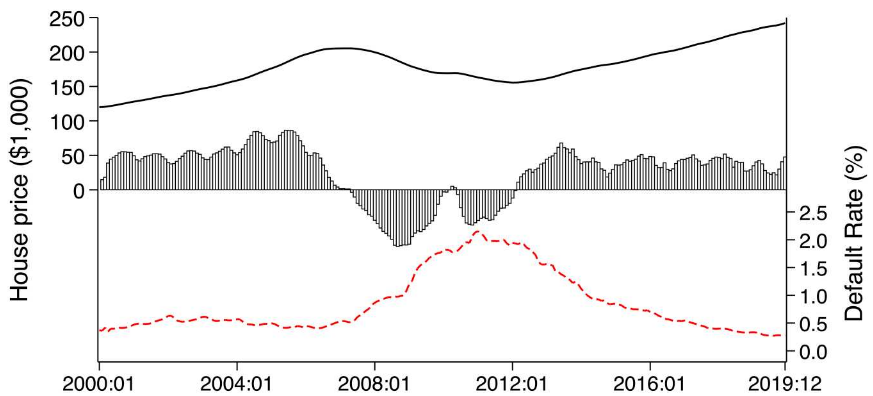

Figure 4. House price and average default rate in the US.
Notes: Monthly dynamics of house prices and average mortgage default rates over the sample period. The black solid line represents the house prices (HP), and the red dashed line shows the US average default rate (DR). The black bars indicate monthly housing returns. The left vertical axis (in thousands of US dollars) corresponds to house prices, while the right vertical axis corresponds to the default rate.
Source: The house price data is from Zillow and the default rate data is provided by CoreLogic.

Table 3. Definition of variables.

Variable (Abbreviation)	Description (Unit)	Data Source
House Price (HP)	Typical value for homes in the 35th to 65th percentile range in US metropolitan statistical areas ($1000)	Zillow
Default Rate (DR)	The ratio of the number of loans in the foreclosure process over the total number of outstanding first lien loans in US Core-based statistical areas (%)	CoreLogic
Income (INC)	Per capita personal income in US metropolitan statistical areas ($1000)	Bureau of Economic Analysis
Mortgage Rate (MTGR)	30-year fixed rate mortgage average in the US (%)	Freddie Mac
Population (POP)	Census bureau midyear population estimate (1000 persons)	Bureau of Economic Analysis
Employment (EMP)	Total nonfarm payroll (1000 persons)	US Bureau of Labor Statistics, Federal Reserve Bank of St. Louis
Building Permit (PERM)	New private housing units authorised by building permits (Units)	US Census Bureau
Ind. Prod. Index (INDP)	Industrial production index (2017 = 100)	Board of Governors of the Federal Reserve System
Producer Price Index (PPI)	Producer price index by all commodities (1982 = 100)	US Bureau of Labor Statistics
S&P 500 Index (SP500)	S&P 500 Index	S&P Dow Jones Indices LLC
Consumer Sentiment (SENT)	University of Michigan Consumer Sentiment (1966: Q1 = 100)	University of Michigan

Notes: This table reports the variables used in the Panel VAR model, along with their abbreviations, descriptions, units and data sources.

Employment and population data are collected at the MSA level, and building permits are recorded at state level. The industrial production index, producer price index and consumer sentiment are available at the national level. Table 4 presents the descriptive statistics of all variables in annual frequency, along with stationarity tests. Table 5 presents the Pearson correlation matrix along with variance inflation factors.

4.4. Panel VAR model

The empirical specification with annual data is closely related to the theoretical model.[10] To account for the panel structure of the empirically observed data and the relatively short panel of annual observations, a panel vector autoregressive (Panel VAR) model, as described by Holtz-Eakin et al. (1988), is estimated. This approach enables the examination of the short-run dynamic interaction between house price returns and mortgage default changes while controlling for the macroeconomic environment. The empirical model is specified as follows.[11]

$$\Delta \boldsymbol{Y}_{i,t} = \begin{pmatrix} \Delta HP_{i,t} \\ \Delta DR_{i,t} \end{pmatrix} = \sum_{j=1}^{p} \boldsymbol{A}_j \cdot \Delta \boldsymbol{Y}_{i,t-j} + \mathrm{B} \cdot \boldsymbol{X}_{i,t} + \boldsymbol{\varepsilon}_{i,t}, \qquad (18)$$

where p is the order of VAR, $i = 1, 2, \ldots, N$ denotes the MSA and $t = 1, 2, \ldots, T$ denotes the year.

This model follows the empirical specification for the simulated data presented in Equation (17). The vector of endogenous variables $\Delta \boldsymbol{Y}_{i,t}$ is the same and includes the house price appreciation rate $\Delta HP_{i,t} = \log(HP_{i,t}) - \log(HP_{i,t-1})$ and the change in the default rate $\Delta DR_{i,t} = DR_{i,\,t} - DR_{i,\,t-1}$. The vector $\boldsymbol{X}_{i,t}$ captures the same fundamental variables, including the growth of household income (ΔINC) and the mortgage rate (MTGR), as well as the following additional controls: growth of population (ΔPOP), employment (ΔEMP), building permits (ΔPERM), industrial production index (ΔINDP), producer price index (ΔPPI), the S&P 500 index (ΔSP500) and consumer sentiment (ΔSENT). The Panel VAR system is estimated with one lag ($p = 1$), which is the optimal number of lags determined by the Bayesian information criterion.

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 & Owen, 1999). Therefore, following Arellano and Bover (1995) and Love and Zicchino (2006), the coefficients $\boldsymbol{A}_j$ and $\boldsymbol{B}$ are estimated using the generalised method of moments (GMM), with the lags of the endogenous variables used as instruments. Furthermore, following the method of Abrigo and Love

Table 4. Descriptive statistics.

Variable	*N* of Obs	Mean	SD	ADF test		Transformation
				Level	Transformed	
Panel A. Recourse States						
HP	2458	156.52	74.44	-4.25	9***	1
DR	2458	0.86	0.72	-5.70	7.72***	2
INC	2458	36.66	9.66	-9.67	46.06***	1
MTGR	2458	5.03	1.20	11.82***	-	0
POP	2458	649.82	1140.37	0.61	16.37***	1
EMP	2458	298.88	551.58	-1.88	25.61***	1
PERM	2458	3614.79	4252.72	-6.06	4.98***	1
INDP	2458	96.81	4.76	0.87	43.77***	1
PPI	2458	178.39	23.64	-1.45	11.15***	1
SP500	2458	1676.71	643.65	-11.75	78.35***	1
SENT	2458	85.35	11.44	-7.46	22.6***	1
Panel B. Non-recourse States						
HP	1702	235.43	138.15	-3.42	9.45***	1
DR	1702	0.94	0.91	-6.20	6.57***	2
INC	1702	39.03	10.00	-8.77	36.54***	1
MTGR	1702	5.02	1.19	8.71***	-	0
POP	1702	797.34	1642.49	0.57	6.83***	1
EMP	1702	348.65	736.43	-2.72	19.73***	1
PERM	1702	4663.13	4139.71	-3.63	7.6***	1
INDP	1702	96.82	4.76	0.00	37.99***	1
PPI	1702	178.47	23.41	-0.21	8.41***	1
SP500	1702	1671.81	642.68	-9.74	64.76***	1
SENT	1702	85.18	11.42	-6.56	20.16***	1

Notes: This table reports the descriptive statistics for the variables used in the Panel VAR model. The 'ADF test' column reports the modified inverse Chi-squared statistic from the Augmented Dickey-Fuller (ADF) tests, performed on both the original level data and the transformed data. *** indicates rejection of the null hypothesis that all panels contain unit roots at the 1% significance level. The 'Transformation' column indicates the transformation applied to the original data: 0 = no transformation, 1 = log difference, 2 = first difference.

(2016), a Helmert transformation is applied to control for the MSA fixed effects.

5. EMPIRICAL RESULTS

This section presents Granger causality tests, impulse responses and forecast error variance decompositions of the bidirectional relationship between default risk and housing returns. For comparison purposes, the estimates of the VAR model for the simulated data are displayed alongside the results of the Panel VAR model.

5.1 Granger causality tests

The Granger causality tests for the interaction between house price appreciation rates and mortgage default changes are reported in Table 6. The columns in *Panel A:* $\Delta HP \rightarrow \Delta DR$ report the Chi-squared statistics for the null hypothesis that house price returns do not Granger-cause mortgage default rate changes, while the columns in *Panel B:* $\Delta DR \rightarrow \Delta HP$ report the corresponding statistics for the null hypothesis that changes in mortgage default rates do not Granger-cause house price returns. The *, ** and *** asterisks indicate a rejection of the null hypothesis at 10%, 5% and 1% significance level, respectively.

Panel A provides strong evidence for Granger causality running from house price returns to default rate changes in non-recourse markets, with the null hypothesis of no Granger causality rejected at the 1% level for both models. In recourse markets, the null hypothesis is only rejected at the 10% significance level in the result of Panel VAR model.[12] Overall, the results are consistent with option-theoretic (or strategic) defaults: borrowers in non-recourse markets are more likely to walk away from their investment when house prices decline.

Panel B shows that changes in default rates Granger-cause house price returns both in recourse and non-recourse states. In all Granger causality tests, the null hypothesis that mortgage default change does not Granger-cause house price depreciation is rejected at least at the 5% significance level. These findings could be explained with direct market equilibrium effects and externalities (Anenberg & Kung, 2014; Campbell et al., 2011).

Table 5. VIF and correlation matrix.

	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A. Recourse States												
(1) ΔHP_{t-1}	1.77	**1.00**										
(2) ΔDR_{t-1}	2.02	**-0.55**	**1.00**									
(3) ΔINC	1.55	**0.17**	**-0.08**	**1.00**								
(4) MTGR	2.35	**0.12**	**0.21**	**0.08**	**1.00**							
(5) ΔPOP	1.54	**0.19**	-0.01	0.00	**0.18**	**1.00**						
(6) ΔEMP	2.86	**0.40**	**-0.35**	**0.49**	**-0.13**	**0.38**	**1.00**					
(7) ΔPERM	2.16	**0.09**	**-0.21**	**0.14**	**-0.40**	**-0.06**	**0.37**	**1.00**				
(8) ΔINDP	2.00	**0.10**	0.02	**0.39**	**-0.08**	-0.04	**0.47**	**0.46**	**1.00**			
(9) ΔPPI	2.03	**-0.08**	**0.40**	0.02	**0.18**	**0.06**	**-0.07**	-0.04	**0.29**	**1.00**		
(10) ΔSP500	2.13	-0.02	**-0.08**	**-0.12**	**-0.47**	**-0.06**	0.02	**0.32**	**0.09**	**0.30**	**1.00**	
(11) ΔSENT	2.22	**-0.09**	**-0.12**	**-0.10**	**-0.54**	**-0.07**	**0.06**	**0.48**	**0.26**	**0.22**	**0.65**	**1.00**
Panel B. Non-recourse States												
(1) ΔHP_{t-1}	2.95	**1.00**										
(2) ΔDR_{t-1}	2.71	**-0.67**	**1.00**									
(3) ΔINC	1.66	**0.36**	**-0.25**	**1.00**								
(4) MTGR	2.96	**0.18**	**0.23**	**0.07**	**1.00**							
(5) ΔPOP	1.49	**0.17**	-0.01	0.03	**0.31**	**1.00**						
(6) ΔEMP	2.95	**0.56**	**-0.51**	**0.54**	**-0.10**	**0.32**	**1.00**					
(7) ΔPERM	3.01	**0.19**	**-0.29**	**0.17**	**-0.44**	**-0.10**	**0.40**	**1.00**				
(8) ΔINDP	2.39	**0.28**	**-0.15**	**0.44**	**-0.08**	-0.04	**0.48**	**0.55**	**1.00**			
(9) ΔPPI	2.05	-0.01	**0.33**	**-0.06**	**0.19**	**0.09**	**-0.10**	0.02	**0.29**	**1.00**		
(10) ΔSP500	2.23	0.02	**-0.10**	**-0.10**	**-0.47**	**-0.13**	0.03	**0.35**	**0.09**	**0.30**	**1.00**	
(11) ΔSENT	2.37	-0.04	**-0.15**	**-0.05**	**-0.54**	**-0.14**	**0.07**	**0.53**	**0.26**	**0.23**	**0.66**	**1.00**

Notes: This table presents the variance inflation factors (VIF) and Pearson's correlation coefficients for the transformed variables used in the Panel VAR model. Variables include the one-year lag of house price returns (ΔHP_{t-1}), the one-year lag of changes in the mortgage default rate (ΔDR_{t-1}), personal income growth (ΔINC), mortgage rate (MTRG), population growth (ΔPOP), employment growth (ΔEMP), building permit growth (ΔPERM), industrial production index growth (ΔINDP), producer price index growth (ΔPPI), S&P 500 index growth (ΔSP500) and consumer sentiment growth (ΔSENT). Bold values indicate statistical significance at the 5% level.

5.2 Impulse response functions

The generalised impulse response functions (GIRFs)[13] show how shocks to the house price appreciation rate impact the future dynamics of mortgage default changes and how the effect of changes in mortgage default propagate over time and affects the dynamics of house price returns. Figure 5 presents the GIRFs of the response of default rate changes to a one-standard-deviation shock to house price return (left panel) and the response of house price appreciation to a one-standard-deviation positive[14] shock to the mortgage default rate change (right panel). The 95% confidence intervals represented in the graphs are based on a Monte Carlo simulation.

Panel A shows the impulse responses of mortgage default rate changes and house price returns based on the VAR regression using simulated data. The response of the mortgage default rate changes 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

Table 6. Granger causality tests.

	Panel A: ΔHP → ΔDR		Panel B: ΔDR → ΔHP	
	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***

Notes: This table reports Granger causality test results examining the dynamic relationship between house price returns (ΔHP) and changes in the mortgage default rate (ΔDR). The first row specifies the direction of Granger causality being tested, while the second row indicates the relevant sample used. The results reported in 'VAR' row are based on the VAR model applied to simulated data, while those in the 'Panel VAR' row come from the Panel VAR model estimated with actual annual data. 'Panel A: ΔHP → ΔDR' reports Chi-squared statistics testing the null hypothesis that house price returns do not Granger-cause changes in the mortgage default rate. 'Panel B: ΔDR → ΔHP' reports the corresponding tests for the reverse direction. *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% significance levels, respectively.

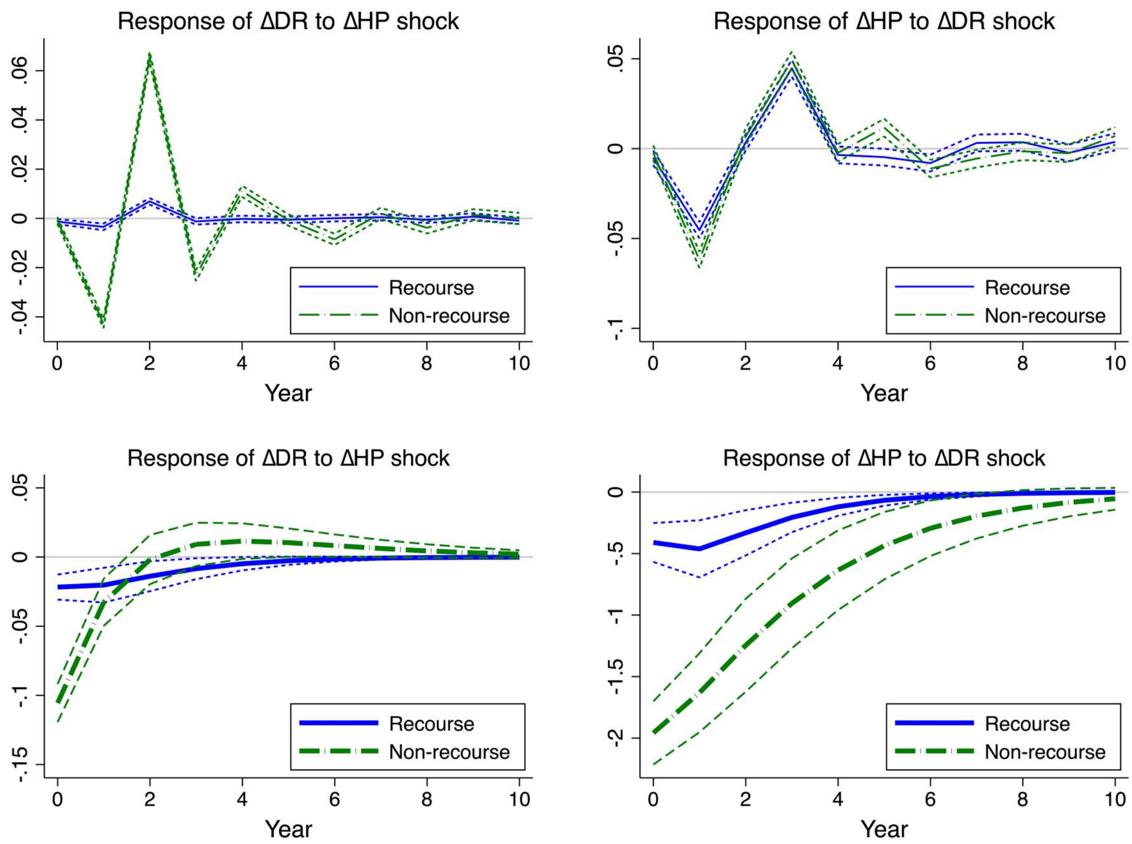

Figure 5. Impulse responses. Panel A: VAR model. Panel B: Panel VAR model.
Notes: Generalised impulse response functions (GIRF) for recourse markets (thick solid lines) and non-recourse markets (long dash-dot lines). Thin dashed lines indicate the 95% confidence bands around the estimated responses. Panel A shows results from the VAR model using simulated data, while Panel B displays results from the Panel VAR model estimated with actual annual data.
Source: Authors' own illustration.

beyond, the impulse responses in both markets tend to converge to zero.

The impulse responses shown in Panel B of Figure 5 are based on the Panel VAR regression using actual data. As in the simulated data, the response of the mortgage default rate changes to a shock to the house price return for a one-year horizon is significantly stronger in non-recourse markets.[15]

The graph in Panel B (right) shows that the responses of the house price returns to shocks in the mortgage default rate changes are significantly stronger in non-recourse states than in recourse states.[16]

Overall, the GIRFs indicate that shocks to house price returns lead to stronger responses of mortgage default rate changes in non-recourse markets. Furthermore, shocks to mortgage default changes result in more pronounced declines in house price returns in non-recourse markets. These effects are more pronounced in the actual data than in the simulation. They corroborate the findings of Ghent and Kudlyak (2011) derived from loan-level data, who report that borrowers are 32% more likely to default in non-recourse states.

5.3 Forecast error variance decompositions

Next, forecast error variance decompositions (FEVD) are analysed to quantify the relative strength of the bidirectional impacts between house price returns and mortgage default risk. Panels A and B in Table 7 report the variance decompositions from the VAR model using simulated data and the Panel VAR model using actual annual data, respectively, across forecast horizons of 2, 4, 6, 8 and 10 years. The 2nd and 3rd columns report the percentage of forecast error variance of default rate changes explained by housing return innovations in recourse and non-recourse states, respectively. The 4th and 5th columns report the percentage of forecast error variance of the housing returns explained by innovations in the default rate changes.

Table 7 shows that the bidirectional impact between house price returns and mortgage default rate changes are uniformly stronger in non-recourse markets and remain robust across all model specifications. These findings are consistent with strategic default behaviour as presented in the theoretical framework.

6. CONCLUSION

This paper examines the interaction between house prices and mortgage defaults in recourse and non-recourse markets. The theoretical analysis demonstrates that house price return shocks generate more defaults in non-recourse

Table 7. Forecast error variance decomposition.

	% of variance of ΔDR explained by shock to ΔHP		% of variance of ΔHP explained by shock to ΔDR	
Years	Recourse	Non-recourse	Recourse	Non-recourse
Panel A. VAR				
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				
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%

Notes: This table reports the forecast error variance decomposition (FEVD) of house price returns (ΔHP) and changes in mortgage default rate (ΔDR), attributing the variation in each variable to shocks in the other variable over horizons of 2, 4, 6, 8 and 10 years. Results in 'Panel A. VAR' are based on the VAR model using simulated data, while 'Panel B. Panel VAR' shows results from the Panel VAR model estimated with actual annual data. The first column indicates the forecast horizon (in years). Columns 2 and 3 report the percentage of ΔDR variance explained by innovations in ΔHP in recourse and non-recourse markets, respectively. Columns 4 and 5 report the percentage of ΔHP variance explained by innovations in ΔDR, also separately for recourse and non-recourse markets.

markets due to strategic default behaviour, and the empirical results from a Panel VAR model confirm these predictions. Moreover, the data reveal that house price returns respond more strongly to shocks in the change in mortgage default rates in non-recourse markets than predicted by the theoretical model. One potential explanation for this finding is that in a non-recourse market, buyers and sellers anticipate further defaults following price declines, and these 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 policymakers and market regulators.

ACKNOWLEDGEMENTS

We thank Petro Gete, Nigar Hashimzade, Erin Hengel, Alla Koblyakova, Michael LaCour-Little, Gianluca Marcato, Elias Oikarinen, Leslie Reinhorn, Lok Man Michelle Tong and participants at the 2018 AREUEA International Conference, the 25th Annual Conference of European Real Estate Society, the 5th Money, Macroeconomics and Finance (MMF) PhD conference, the MMF and Cass Business School conference on Investment, Funding and Industrial Policy, the 2018 FMA Annual meeting, the 2019 FMA European Conference, the 2024 FMARC Conference, and the 2024 ReCapNet conference for their comments.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from a commercial data provider (CoreLogic, www.corelogic.com). Restrictions apply to the availability of these data, which were used under license for this study. Additional data used in this study were collected from resources available in the public domain. These data are available from the corresponding author upon request.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

FUNDING

This project was supported by the DUBS 4* Fund and by the Department of Finance at Durham University Business School.

NOTES

1. Four is the smallest number of periods allowing the modelling of the decision of households to buy, then to default on their mortgages, for a defaulted home to be foreclosed and for non-defaulting households to decide at a later period to sell their house and relocate for reasons external to the model.
2. In the subsequent simulation, the mortgage period is set at $T = 30$ years which corresponds to the dominant fixed rate home mortgage product in the US (Kish, 2022). While this choice is appropriate for the US, the mortgage rates in some other countries are fixed for much shorter periods. Koblyakova et al. (2014) show that in the UK the duration of a mortgage's fixed interest rate is dependent on the demographic characteristics of borrowers and varies by region.
3. See Zevelev (2014, p. 73) for the closed form solution of a utility maximisation problem with a CES utility.
4. Mortgage default leads to a foreclosure and it takes one period for a foreclosed home to be sold. While defaulting households of age $a = 2$ leave the market, non-defaulting households remain in their homes until the age of $a = 3$.
5. A similar assumption of fixed supply is also a feature of the life cycle model by Guren et al. (2021), where the focus is on mortgage payment design rather than recourse.
6. According to Zillow (2024) most lenders require a minimum down payment of 5% on a conventional loan.
7. As a robustness check, the VAR model is estimated with a one-lag specification – the same as the optimal lag length identified for the Panel VAR system using actual annual data – and the results remain consistent.
8. 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. 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.

9. These time series are downloaded from https://www.zillow.com/research/data/. Since the Metro regions defined in the Zillow data do not fully align with the MSA definitions used in other data sources, we match each Zillow Metro region to an MSA by comparing both the Metro region name and its corresponding US state to the first principal city and state of each MSA.

10. In the Appendix in the online supplemental data, an extension of the empirical model is estimated with monthly data which allows for cointegration between house prices and default rates by using a panel vector error-correction model (Panel VECM).

11. A vector autoregressive model with a similar structure, where exogenous variables enter in the regression equation contemporaneously, has been analysed by Yan et al. (2016). The panel specification used here also takes into account the cross-sectional dependence across MSAs. The system stationarity of the model is confirmed by checking the eigenvalue of the companion matrix.

12. In the simulated data, a bi-directional Granger causality is observed. This effect is most likely due to the permanent income shock $v = t$ which affects multiple cohorts of homeowners.

13. 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 criticism of the traditional approach).

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

15. The effects are quantified by calculating the cumulative impulse responses. In a recourse market, a one standard deviation shock to house price returns (3.85%) is associated with a reduction in the mortgage default rate change of 0.042% after one year, 0.056% after two years and 0.075% after ten years, as measured by the cumulative impulse response function. In comparison, in a non-recourse market, a comparable shock (5.16%) is followed by decreases in the default rate change of 0.138%, 0.140% and 0.085% after one, two and ten years, respectively.

16. In recourse markets, a one standard deviation shock to the change in the default rate (0.204%) causes the house price return to drop by 0.87% in one year, 1.20% in two years and 1.67% in ten years. In comparison, in non-recourse markets, a one-standard-deviation shock to the change in the default rate (0.278%) decreases the house price growth rate by 3.59%, 4.83% and 7.57%, respectively.

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