Mortgage Securitization and Information Frictions in General Equilibrium

Salomon Garcia-Villegas*

November 2024

Abstract

We develop a model of the U.S. housing finance system that delivers an equilibrium connection between the securitization and mortgage credit markets. An endogenous securitization market efficiently reallocates illiquid assets, increases liquidity to fund mortgage lending, and lowers mortgage rates for households. However, its benefits are hindered by originators' private information about loan quality, which leads to adverse selection in securitization. Fluctuations in household credit risk induce mortgage credit expansion and contractions through the securitization liquidity channel. Information frictions and liquidity frictions on credit supply generate a multiplier effect of household shocks. Applying the model to the Great Financial Crisis, we quantify that information frictions amplified the observed mortgage credit contraction. Our assessment of the post-GFC securitization market indicates that pricing credit guarantees in way that reflects the amplification of information frictions may enhance the financial stability of the system—reducing the volatility of prices and quantities and the probability of a market collapse.
Keywords: Credit intermediation, mortgage markets, adverse selection, DSGE, private information, liquidity frictions.
JEL codes: D5, D82, G21, G28

*Banco de España, email: salomon.garcia@bde.es. Special thanks to my PhD advisors V.V. Chari, Ellen R. McGrattan, and Anmol Bhandari, for their invaluable guidance. I am grateful to Mark L. J. Wright, Larry Jones, Loukas Karabarbounis, Christopher Phelan, David Martinez-Miera, Rodrigo Heresi, Vladimir Asriyan, Rafael Repullo, Javier Suarez, and two anonymous referees for their feedback. I thank participants of the seminars at the University of Minnesota, CEMFI, University of Edinburgh, the Federal Reserve Bank of Minneapolis, University of Copenhagen, Michigan State University, SUNY-Buffalo, Lancaster University, and Bank of Spain. Also, thanks to conference participants at the EEA 2021, IFABs 2021, MadBar 2021, CEMLA 2021, and EEA-ESEM 2021, 2022, and the Society of Economic Dynamics 2023. The views expressed herein are those of the author and do not necessarily reflect the views of the Banco de España or the Eurosystem.

1 Introduction

The mortgage market in the United States comprises two markets: the mortgage credit market, where loan originators issue mortgages to households, and the securitization market, where mortgages are sold, bundled, and transformed into mortgage-backed securities (MBS). Securitization allows banks to free up capital, expanding mortgage credit supply, and has become the primary funding source for originators; from 2000 to 2019, 70% of residential mortgages were sold or securitized within the first year of origination. However, this funding source is volatile and can rapidly expand or collapse abruptly, as observed during the credit cycle of the 2000s, disrupting mortgage credit availability—a key macroeconomic variable and a policy objective in the United States.

In this paper, we develop a quantitative model of the U.S. housing-mortgage market to examine how information and liquidity frictions in securitization affect mortgage lending and households' access to mortgages and housing. While information frictions in the mortgage origination and securitization chain are well-documented and have motivated theoretical models explaining abrupt declines in security trading, their effects on mortgage market aggregates and household welfare remain less explored.[1] Our model fills these gaps by offering a framework to quantify the role of securitization frictions in shaping mortgage credit dynamics. We apply this framework to analyze the contraction of U.S. residential mortgage credit following the Global Financial Crisis (GFC); identifying the household shocks driving the observed dynamics, assessing which frictions amplified these shocks and to what degree, and examining their implications for evaluating current government mortgage policies.

We begin with a stylized model of credit intermediation, where lenders face default on their legacy loans and heterogeneous loan origination costs, extended to include a securitization market where lenders trade pools of loans à la Kurlat (2013). The model establishes an equilibrium link between the securitization and credit markets. For lenders, differences in origination costs and limited liquid funds generate motives for trading in the securitization market. When trading, lenders split into lender-sellers and lender-buyers. Lenders with low origination costs have incentives to raise liquidity by selling their legacy loans and originating new ones. In contrast, lenders with a high origination cost can make more profits by investing through the purchase of securities. Without information frictions, securitization allows lenders with varying liquidity needs to reallocate legacy loans, directing liquidity to the lowest-cost lenders. Such reallocation improves the efficiency of credit funding, lowers lending rates, and increases credit. However, this setup fails to account for

[1] We focus on information frictions between loan originators and MBS investors; in particular, the empirical evidence indicates that originators are better informed about loan quality and exploit this asymmetry, leading to adverse selection in secondary markets (Downing et al., 2008; Keys et al., 2010; Piskorski et al., 2015a; Adelino et al., 2019). On theoretical grounds, building on Akerlof (1970), a growing literature on dynamic adverse selection (Guerrieri and Shimer, 2014; Chari et al., 2014), has advanced our understanding of how such frictions can lead to sharp declines or even collapses in security trading.

the positive correlation between securitization and credit volumes observed in the data. Introducing private information about loan quality leads to adverse selection in securitization; all lenders sell low-quality (likely to default) loans while some retain high-quality ones. As default rates rise, adverse selection ensures securitization volumes fall, producing a positive correlation with credit volumes but reducing the benefits of securitization. During periods of high default, this mechanism amplifies declines in securitization volumes and prices, triggering sharp, non-linear contractions in credit—consistent with the dynamics observed in the GFC.

To quantify the role of securitization frictions in accounting for aggregate mortgage credit and housing dynamics, we develop a general equilibrium model of financial intermediation along standard macro housing models with collateral constraints (Iacoviello, 2005) and long-term debt (Garriga et al., 2017). In this setup, an impatient borrower household takes on long-term mortgages to finance housing services and non-durable goods, driven by aggregate income and housing risk. Mortgage credit supply is determined by a continuum of patient lenders operating with private equity and a legacy portfolio of mortgages. We incorporate key features of the U.S. mortgage market; first, borrowers can endogenously default, determining the quality of loans held by lenders. Second, lenders face heterogeneous origination costs, capturing differences in loan origination technology and lending opportunities. Third, lenders are financially constrained and privately informed about loan quality, introducing liquidity and information frictions. Finally, as in the stylized model, a securitization market, affected by adverse selection, allows lenders to sell loans or purchase securities.

The quantitative model delivers boom-bust cycles in mortgage credit driven by household income and housing risks. Persistent adverse income or housing valuation shocks can trigger a surge in mortgage defaults, endogenously affecting the composition of high- and low-quality loans in lenders' portfolios. As defaults rise, information frictions in securitization become more severe, leading security buyers to expect a higher share of non-performing loans in securitized portfolios. This reduces securitization volume and drives down security prices. In turn, loan sellers face an endogenous liquidity shortage as they are unwilling to sell loans at depressed market prices. Given lenders' limited access to debt markets, credit supply to households contracts, worsening the household balance sheet and creating an amplification loop that prolongs the downturn in mortgage credit cycles. In equilibrium, information frictions generate a multiplier effect of adverse household shocks, amplifying their aggregate effects in the mortgage market..[2]

A quantitative test of the model shows it can replicate the dynamics observed during the GFC. From 2008 to 2013, aggregate mortgage credit contracted by 40%, while aggregate MBS issuance declined by 30%, as shown in Figure 1 in Section 1.1. When households in the baseline model experience the same sequence of income shocks observed in the data, along with a sequence of

[2]A financial accelerator (Bernanke and Gertler, 1989; Bernanke et al., 1996) effect emerges in our framework; endogenous developments in securitization amplify and propagate household shocks throughout the mortgage credit market and the rest of the economy.

housing valuation shocks calibrated to endogenously match the mortgage default patterns during this period, the model reproduces two-thirds of the contraction in mortgage credit and the entire contraction in MBS issuance. A counterfactual model without securitization information frictions explains only half of these contractions. These results suggest that information frictions amplified the GFC mortgage credit contraction by a factor of 1.2 to 1.3. Two aspects of the data determine the magnitude of the multiplier: (i) the reliance on securitization liquidity for issuing new loans, calibrated by the fraction of loans securitized by originators; (ii) the cross-sectional moments of the distribution of mortgage lending across loan originators, which the model internally matches. On average, one-fifth of the model's predicted decline in mortgage lending arises from the amplification effect of information frictions, while housing and income shocks account for the rest. This analysis contributes to understanding the factors at play during the GFC, showing how problems in the securitization market can spill over to the credit market and account for mortgage credit and housing dynamics at the aggregate level.

The government's involvement in the securitization market is captured by a credit guarantee that compensates buyers of securities for the losses associated with household default. The government finances this policy by imposing a distortionary tax on mortgage originators and lump-sum taxes on households. The aim of the policy is to encourage a stable demand for securities, thereby increasing the volume of security issuance and the volume of credit that is intermediated to households. In this sense, the policy resembles the role of the credit guarantees provided by government-sponsored entities (GSEs) to buyers of MBS.[3]

We assess the government's stabilization role in the securitization market through a credit guarantee policy that compensates security buyers for losses from household defaults. These guarantees are funded by fees on mortgage originators, taxes on lenders, and lump-sum taxes on households. The policy aims to stabilize demand for securities by reducing buyers' exposure to credit risk, thereby mitigating the severity of information frictions in securitization.

We take a macroeconomic perspective and compare the post-GFC economy, where all MBSs carry a credit guarantee with fees similar to those observed after 2012, to the pre-GFC economy, where only a fraction of MBSs were guaranteed, and fees were lower (2006 levels). Our findings show that the post-GFC setup results in lower volatility in securitization and credit volumes, more stable interest rates, and improved household credit access. However, the policy continues to generate significant deficits, suggesting that credit guarantees remain underpriced. This result indicates that pricing credit guarantees to reflect the amplification effects of information frictions may require higher guarantee fees than the currently observed ones. We estimate the break-even price for credit guarantees and find that aligning fees with this level could reduce mortgage defaults, housing equity losses, and tax burdens, ultimately improving welfare for both borrowers and lenders. Finally, we

[3]The GSEs (Freddie Mac and Fannie Mae) purchase mortgages from originators, bundle them into MBS, and insure buyers against borrower credit risk.

also discuss the limitations of credit guarantees as a stabilization tool in their current form.

Layout. The rest of this introduction briefs on the related literature. In Section 1.1, we present evidence of the mortgage credit boom-bust experience in the United States. Section 2 presents a stylized model that lays out the main mechanism and theoretical insights of the quantitative model introduced in Section 3. Section 4 presents the quantitative analyses, and Section 5 concludes.

Related Literature. This paper contributes to the literature that incorporates financial frictions into macro housing models to understand aggregate dynamics in mortgage and housing markets. Previous studies have emphasized channels such as collateral constraints on borrowers (Iacoviello, 2005; Iacoviello and Neri, 2010), the interaction of borrower constraints and exogenous saving shocks (Favilukis et al., 2017), credit supply constraints (Justiniano et al., 2015, 2019), and financial market segmentation (Garriga et al., 2019). We show that information frictions in securitization combined with liquidity frictions on the supply side of credit markets can amplify mortgage credit cycles. Much of this literature focuses on the dynamics surrounding the GFC. For instance, Justiniano et al. (2015, 2019) argue that mortgage lending constraints, which restrict lenders' access to funding, were more significant than demand-side factors in explaining the rapid growth of mortgage debt and the housing boom of the 2000s— first documented by Mian and Sufi (2009).[4] Our model complements Justiniano et al. (2019) by providing microfoundations for lending constraints, introducing securitization as a key liquidity source for mortgage lenders. It predicts that access to securitization expands credit supply and lowers mortgage interest costs, with significant effects on credit and house prices in equilibrium. Predictions that are also consistent with the segmented financial market framework in Garriga et al. (2019).

A vast body of literature documents the presence of private information in the mortgage issuance and securitization process, with particular emphasis on lenders' private knowledge of loan quality.[5] Such information frictions lead to adverse selection in securitization, a central mechanism in our framework. We build on macroeconomic models that incorporate adverse selection in financial markets, such as Kurlat (2013) and Bigio (2015), to investigate how this mechanism shapes the joint dynamics of securitization and mortgage credit volumes. To achieve this, our model endogenizes asset quality through borrowers' default dynamics, a feature not present in the above models that treat asset quality as exogenous.[6] Our work also shares elements present in theoretical models

[4] On the credit demand side, Kaplan et al. (2020) and Chodorow-Reich et al. (2023) examine the role of house price expectations in driving housing booms and busts.

[5] Downing et al. (2008), Keys et al. (2010), Elul (2011), and Adelino et al. (2019) consistently find that mortgage originators tend to retain higher-quality loans while selling first the lower-quality ones, generating scope for adverse selection in securitization. For a detailed review of private information in the MBS market and its implications, see Shimer (2014).

[6] Vanasco (2017) and Caramp (2019) study the interplay of endogenous asset quality production and adverse selection in secondary markets.

(Guerrieri and Shimer (2014), Chari et al. (2014), Asriyan (2020), Garcia-Villegas (2023)) that highlight how adverse selection reduces liquidity provision in asset markets. We apply these insights to the mortgage securitization market and show how endogenous liquidity shortages spill over into the credit market and exacerbate borrowers' financial conditions, creating a feedback loop that amplifies mortgage credit cycles.

This paper also contributes to the literature on government policies in the mortgage and housing markets. Elenev et al. (2016) develop a housing macro model with banks to show that underpriced guarantees during the 2000s credit boom, combined with deposit insurance, encouraged excessive bank leverage. In contrast, our model focuses on adverse selection in securitization rather than moral hazard from bank leverage. We evaluate the trade-off between reducing the costs of information frictions, which enhances lending efficiency, and the fiscal cost of financing credit guarantees. Our findings also demonstrate that credit guarantees were significantly underpriced before the GFC. Moreover, we highlight the stabilization benefits of pricing guarantees to adequately reflect the amplification effect of household shocks associated to frictions in securitization.

1.1 Institutional Features in The Credit and Securitization Markets

Securitization allows lenders to diversify their exposure to borrowers' default risk and reduce cash-flow(income) risk by spreading the risk across a pool of mortgages.[7] By transferring these pools to investors, securitization transforms illiquid mortgages into liquid funds, enabling lenders to issue new mortgages and expand credit supply to borrowers. Our model in Section 3 focuses on the liquidity provision role of securitization while abstracting from its risk pooling aspect.

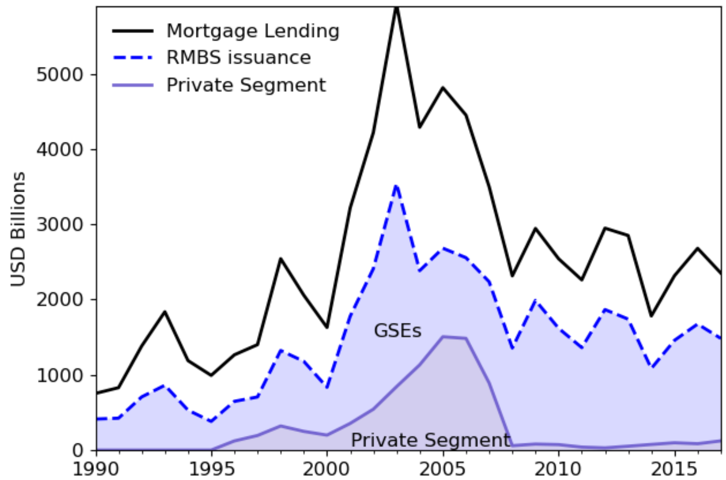
Mortgage originators' reliance on securitization for liquidity is known as the originate-to-distribute model of mortgage funding. Figure 1 illustrates how mortgage loan issuance and RMBS issuance move closely together. When demand for securities rises, originators quickly securitize loans, freeing resources to fund new mortgages. Conversely, securitization downturns create liquidity shocks; originators must hold loans longer, potentially contracting mortgage credit if they lack capital or alternative funding (Loutskina, 2011; Calem et al., 2013). This strong correlation supports the prevalence of financial constraints among originators and the importance of securitization to relax them (Loutskina and Strahan (2009)), a key feature also present in our quantitative model.

The securitization market features a distinction between Government-Sponsored Enterprise (GSE) MBS and private-label MBS. GSE-issued MBSs carry a credit guarantee that ensures principal and interest payments to investors in case of borrower defaults, whereas private-label MBSs lack such government guarantees.[8] This feature has been central in sustaining issuance in the GSE segment,

[7] Gorton and Metrick (2013) provides an in-depth analysis of securitization's role in lowering capital costs, creating safe assets through risk pooling, and enabling financial specialization.

[8] The GSEs are Fannie Mae (Federal National Mortgage Association), Freddie Mac (Federal Home Loan Mortgage Corporation), and Ginnie Mae (Government National Mortgage Association). GSE mortgage-backed securities differ

Figure 1: Credit and securitization mortgage markets



Source: Mortgage lending comes from aggregating volume of new mortgage issuance during the first year of origination across all reporter institutions in the HMDA database. RMBS issuance is from SIFMA (Securities Industry and Financial Markets Association). "GSE" corresponds to RMBS issuance by Freddie Mac and Fannie Mae. "private segment" corresponds to issuance by private institutions. Amounts are in USD real terms, base year 2015.

as shown in Figure 1, where the light-shaded area represents the GSE segment and the darker-shaded area depicts the private segment. While the private segment collapsed in 2007 and has not recovered, GSE MBS issuance remained substantial following the GFC. Our quantitative model in section 4 accommodates both segments by modeling government guarantees as either full or partial. It also explores the differing dynamics of securitization and credit markets under fully guaranteed versus partially guaranteed securities. Additionally, in section 4.4, we consider a full credit-guaranteed security market to assess how frictions in securitization influence the pricing of government guarantees.

2 A Stylized Model

We start by presenting a simplified two-period model of financial intermediation that can be solved by hand. We use this simplified model to highlight the role of the securitization market and its connection with credit market outcomes and to explain the main amplification mechanism of the quantitative model presented in Section 3.

Environment. Consider an economy with a continuum of risk-neutral lenders of mass one operating in a credit market across two periods: $t = 0, 1$. In period 0, lenders use their resources to

from those in the private segment in other relevant dimensions. They are backed by mortgages subject to stricter issuance criteria, offer greater liquidity, and typically provide lower interest rates to investors, reflecting their perception as lower-risk assets. See Vickery and Wright (2013) originate loans, while in period 1, they consume all their accumulated wealth. Lender have linear preferences over consumption. At time zero, each lender j begins with a cash endowment $w > 0$ and a legacy loan portfolio $b_0^j > 0$. Legacy assets represent previous loans extended to (unmodeled) borrowers, maturing in period 1. The lender also observes her idiosyncratic cost z^j for originating new loans n^j. This idiosyncratic origination cost distributes identically and independently (iid) across lenders with cumulative distribution function $F(z)$ in the support $[\underline{z}, \bar{z}]$.[9]A lender's budget at time zero is $z^j n^j q = w$, where $q > 0$ represents the discounted price of new loans, which all lenders take as given as they are assumed to operate in a perfectly competitive credit market. Legacy assets are subject to aggregate default risk: a fraction $\lambda \in (0, 1)$ of them defaults and pays nothing at $t = 1$. We assume that lenders hold a diversified legacy portfolio similarly exposed to aggregate default; hence, default effectively splits a lender's portfolio into a performing and non-performing fraction. The performing legacy plus the newly originated loans accumulate into the next period, the law of motion of legacy assets is $b_1^j = (1-\lambda)b_0^j + n^j$. To keep the model simple, we abstract from modeling borrowers and instead, assume that the aggregate demand for new loans is given by $N^D(q) = \Theta q^{\frac{1}{\epsilon}}$, where $\Theta > 0$ is a demand shift parameter, $\epsilon > 0$ governs the elasticity of credit demand.

Lending without securitization. In this environment, loan origination through z is the only technology available to lenders to transfer resources to the next period. The maximization problem of the lender is: $\max_{\{n\}} c_1 \quad \text{s.t} \quad z^j n^j q = w$, respecting the law of motion of legacy assets. Maximizing consumption is equivalent to maximizing the size of the next period's portfolio. Characterizing this problem is trivial. Each lender invests all her resources in operating her lending technology and originates $n^j = \frac{w}{z^j q}$ given their z^j cost. Aggregate credit supply is given by the integral of individual lending decisions across all lenders $N^S(q) = \int_{\underline{z}}^{\bar{z}} \frac{w}{zq}\, \mathrm{d}F(z)$. Notice that aggregate credit supply is limited by the liquid funds available to lenders given by their cash endowment.

The equilibrium price of credit can be analytically solved from the credit market clearing condition for new loans $N^D(q) = N^S(q)$, which leads to:

$$q^{NS} = \left(\frac{w}{\Theta} \int_{\underline{z}}^{\bar{z}} \frac{1}{z}\, \mathrm{d}F(z) \right)^{\frac{\epsilon}{1+\epsilon}}, \tag{1}$$

where q^{NS} is the discounted price in an economy with no access to securitization. Since each lender operates their lending technology, the price of credit is a function of the average origination cost across all lenders. The gross lending rate R to a borrower is directly related to the average origination cost as $R = \frac{1}{q}$; higher origination costs lead to higher lending rates.

[9]We interpret z as capturing heterogeneity in loan underwriting, screening, and lending opportunities across loan originators. This approach is analogous to Kiyotaki and Moore (2005); Kurlat (2013) random arrival of investment opportunities and to introducing heterogeneous intermediation costs proportional to loan returns as in Boissay et al. (2016).

The key friction in this simple environment is lenders limited access to capital markets; if they could trade away their differences in origination costs, for instance, by issuing one-period state-contingent contracts among them, only the lowest-cost lender would operate while the rest of the lenders would finance her. The equilibrium price of credit would depend only on the origination cost of the lowest-cost lender, leading to $q^\star = \left(\frac{w}{\Theta}\frac{1}{\underline{z}}\right)^{\frac{\epsilon}{1+\epsilon}}$. Such an equilibrium outcome is efficient as it minimizes intermediation costs.

Lending with securitization and complete information. We now partially relax capital market incompleteness by allowing lenders to trade legacy assets in a securities market. Our approach to model security trading is based on Kurlat (2013)'s theory of asset creation and reallocation, where traders have asymmetric information about the quality of traded assets. To build intuition, we start by extending our credit model to include a securities market operating under complete information about the quality of traded loans, i.e., all lenders can perfectly identify the performing status of traded loans. Without information asymmetries, non-performing loans are publicly identified and can be thought of as not traded or traded at price zero. The main role of the securities market is to transform illiquid legacy loans into homogeneous securities that can be transferred and accumulated; this is the securitization process. A security should be understood as a representative bundle of all loans sold into securitization.

Access to the securities market allows every lender to buy securities d and sell legacy loans s at a pooling price $p > 0$. The law of motion of legacy assets for lender j becomes:

$$b_1^j = (1-\lambda)b_0^j + n^j - s^j + d^j, \tag{2}$$

where her loan sales and security purchases satisfy: $s^j \in [0, (1-\lambda)b_0]$ and $d^j \geq 0$. Note that legacy sales are subtracted from the stock of legacy loans net of non-performing, while security purchases accumulate over time as new loans do. At time $t = 0$, the budget constraint of lender j becomes:

$$n^j z^j q + pd^j = w + ps^j, \tag{3}$$

where the new term on the right-hand side represents cash inflows from legacy sales, and cash outflows from security purchases are now recorded on the left-hand side.

How do lenders choose $\{d, s, n\}$? Lenders maximize consumption by solving the linear problem: $\max_{\{n,d,s\}} c_1 \quad \text{s.t} \quad z^j n^j q + pd^j = w + ps^j$, see Appendix A.1 for derivation details. Their trading decisions are characterized by comparing their origination cost z^j to an endogenous market cut-off z^{CI}, which in equilibrium is given by the ratio of the securitization price to the discounted price of credit $z^{CI} = \frac{p}{q}$. Lenders with $z^j < z^{CI}$ sell all their legacy loans and originate new ones, while lenders with $z^j > z^{CI}$ retain their legacy, purchase securities, and originate zero new loans. This characterization makes lenders classify into two groups when trading in the securitization market: lenders-sellers and lenders-buyers.

The securitization technology allows lenders with heterogeneous valuations of their legacy portfolio— given their heterogeneous origination cost — to benefit from trading legacy loans. Low-cost lenders can now convert illiquid assets into liquid funds by selling their legacy portfolio; these lenders have incentives to do so because they can originate new loans at a lower cost. In turn, high-cost lenders have a high valuation of their legacy portfolio, so they retain it. For them, the cost of originating new loans is higher than that of investing through securities; hence, they choose to buy securities as an alternative to costly origination. In sum, securitization increases the efficiency of credit funding by reallocating illiquid assets toward those whose willingness to hold them is higher and by channeling liquidity to the most efficient (lowest-cost) lenders— the essence of the securitization liquidity channel.

We now show how accessing securitization impacts prices and quantities in the credit market. Given the tractable structure of our simplified model, we can derive analytical expression for the aggregate supply of legacy loans $S(p,q) = \int_{\underline{z}}^{\frac{p}{q}} s \; \mathrm{d}F(z) = (1-\lambda)b_0 F\left(\frac{p}{q}\right)$, the aggregate demand of securities $D(p,q) = \int_{\frac{p}{q}}^{\bar{z}} d \; \mathrm{d}F(z) = \left(1 - F\left(\frac{p}{q}\right)\right)\frac{w}{p}$, and the aggregate supply of credit $N(p,q) = \int_{\underline{z}}^{\frac{p}{q}} n(z) \; \mathrm{d}F(z) = \int_{\underline{z}}^{\frac{p}{q}} \frac{w+p(1-\lambda)b_0}{zq} \; \mathrm{d}F(z)$. Solving for equilibrium allocations and prices $\{p^{CI}, q^{CI}\}$ that clear both markets amounts to solving the joint system:

$$D(p,q) = S(p,q) \tag{4}$$

$$N^D(q) = N^S(p,q), \tag{5}$$

where credit demand $N^D(q)$ is given by the same function specified before. The system (4)-(5) reflects the equilibrium connection between the securitization and credit markets. By explicitly modeling such a connection, our model shows how allocative efficiency gains from securitization lead to an increase in aggregate credit supply and to a reduction of credit intermediation costs— since in equilibrium, only the lowest-cost lenders originate new loans —which implies a more favorable price of credit for borrowers than in the absence of securitization. This intuition is formalized below in Proposition 1.[10]

Proposition 1. *Access to securitization increases credit supply and lowers loan rates relative to an economy where lenders operate without securitization, i.e., the discounted price of credit satisfies* $q^{CI} > q^{NS}$.

Securitization with private information. We now introduce information asymmetries among lenders by assuming that, at the beginning of period $t = 0$, each lender can privately predict and identify within their legacy portfolio the fraction of loans that will non-perform. The information asymmetry disappears by the end of the period, and the holders of non-performing loans recover

[10]See Appendix A.3 for a formal proof. Vickery and Wright (2013) and Fuster and Vickery (2014) provide empirical support for these mechanisms, finding that loan securitization is associated with an inflow of liquid funds and lower interest rates in the residential mortgage market.

nothing.[11] The securitization market operates as before: lenders may sell legacy loans or buy securities at a pooling price $p > 0$. However, because of private information, lenders can now sell loans selectively; let s_H represent sales of loans a lender identifies as of high-quality— those that will likely perform, and s_L for low-quality loans— those loans that will likely non-perform. At $t = 0$, the budget set of lender j is:

$$n^j z^j q + pd^j = w + p(s_H^j + s_L^j), \tag{6}$$

where legacy sales satisfy portfolio restrictions: $s_H^j \in [0, (1-\lambda)b_0^j]$ and $s_L^j \in [0, \lambda b_0^j]$. We keep track of the total fraction of low-quality loans sold into securitization and represent it by the endogenous function $\mu(p, q)$:

$$\mu(p, q) = \frac{S_L}{S(p, q)}, \tag{7}$$

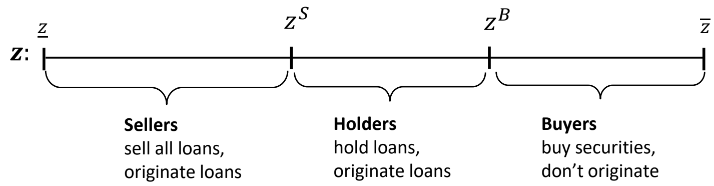
where $S(p, q) = S_H + S_L$ denotes aggregate sales of loans, S_H and S_L denotes aggregate loan sales of each quality—we have omitted the price dependence. This function is useful to account for the impact of information frictions on securities accumulation. Since a security is a representative bundle of all loans sold— of high and low-quality, and given that low-quality loans do not accumulate over time, only a fraction $1 - \mu(p, q)$ of purchased securities will effectively accumulate to the next period. A lender's law of motion of legacy becomes:

$$b_1^j = (1-\lambda)b_0^j + n^j - s_H^j + d^j(1 - \mu(p, q)). \tag{8}$$

The characterization of lenders trading decisions $\{n, d, s_H, s_L\}$ is similar to the previous setup, see Appendix A.2. The main difference is that lenders may now sell loans selectively due to private information. At any $p > 0$, all lenders have incentives to sell all their low-quality loans first, choosing $s_L^j = \lambda b_0^j \quad \forall j$. In equilibrium, the rest of decisions are characterized according to cutoffs $\{z^S,\ z^B\} \equiv \left\{\frac{p}{q},\ \frac{p/q}{1-\mu(p,q)}\right\}$ that split lenders into three groups according to their cost $z \in [\underline{z}, \bar{z}]$, as shown in Figure 2. Lenders with $z \in \left[\underline{z},\ z^S\right)$: sell all their legacy loans, don't buy securities, and use all their resources to originate new loans. Lenders with $z \in \left(z^B,\ \bar{z}\right]$ retain their high-quality legacy, buy securities, and don't originate new loans. Lenders with $z \in \left[z^S,\ z^B\right]$ retain their high-quality legacy, don't buy securities, and originate new loans. Hence, lenders self-classify into lender-sellers and lender-buyers and lenders-holders, respectively.

[11] In the quantitative model where we aim to represent mortgage loans, these assumptions are relaxed in two dimensions; first, lenders predict and identify non-performing loans imperfectly, and second, defaulting loans feature a positive recovery value upon foreclosure of the loan's collateral.

Figure 2: lenders' trading groups with private information



When lenders have private information about their legacy quality, an adverse selection problem, as in Akerlof (1970), arises in the securitization market because all lenders have incentives to sell low-quality loans. In equilibrium, all lenders sell their low-quality loans first, and only lender-sellers also sell their high-quality loans, reducing the average quality of the securitized loan pool. Information frictions generate a wedge between the relative price of securitized loans and the effective cost of buying securities: although a buyer pays p for a security, the effective cost amounts to $p/(1-\mu)$. Such a wedge discourages some lenders from selling high-quality loans and buying securities, effectively disrupting the allocative efficiency of securitization and thereby increasing intermediation costs. In the aggregate, there is less liquidity available to fund new credit and lending rates are higher than in the absence of information frictions.

Kurlat (2013) shows that, due to adverse selection, the securities market may collapse or become inactive whenever the traded fraction of low-quality assets is too high.[12] On the other hand, an inactive securitization market implies that there is no positive price that clears supply and demand. In such a scenario, the credit market still operates but the aggregate supply of credit will be given by integrating lending decisions across all lenders that originate new loans using their origination technology, as we did in the model without access to securitization. Hence, since the securitization market can be active or inactive, credit supply becomes contingent on its trading equilibrium outcome. Proposition 2 summarizes this insight. As before, we can derive analytical expressions for trading policy functions and the aggregates in each market, see Appendix A.4 for details. Equilibrium prices (p, q) are obtained by solving the joint system of equations given the clearing conditions of the credit and the securitization markets, similar to the system (5)-(4).

[12]A characteristic also present in models of static (Akerlof (1970), Stiglitz and Weiss (1981)) and dynamic adverse selection (Guerrieri and Shimer (2014), Chari et al. (2014)). Our framework goes one step further by providing an equilibrium connection between securitization and the credit markets, and showing that the economy can transition between states in which the securitization market is active and inactive.

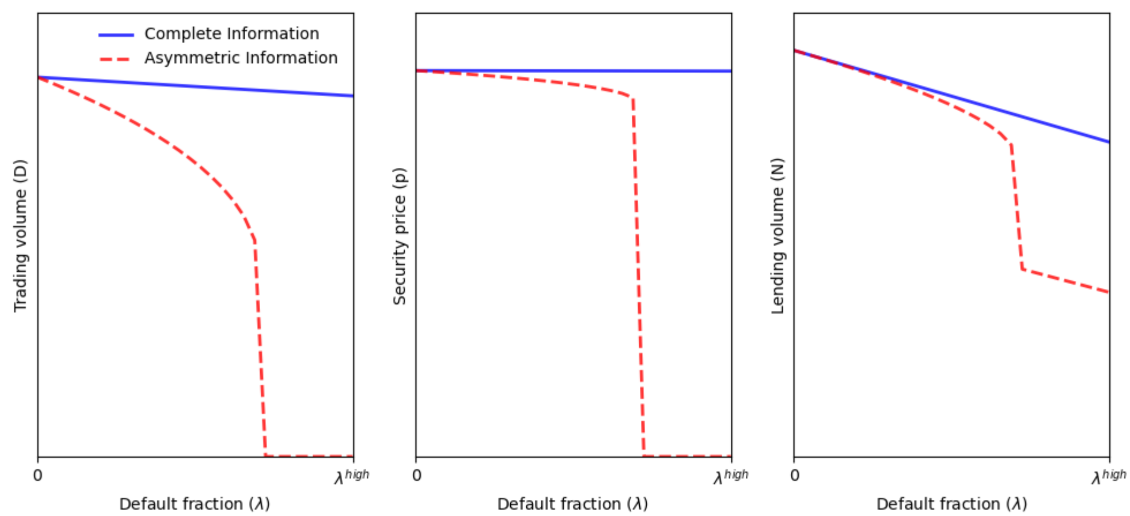
Proposition 2. *Credit supply is contingent on the equilibrium outcome achieved in the securitization market. The credit supply function is given by*

$$N^S(p,q) = \int_{\underline{z}}^{z^\star(p,q)} n(z^*)\ dF(z) \quad \textit{with} \quad z^\star(p,q) = \begin{cases} z^B & \textit{if active securitization market,} \\ \bar{z} & \textit{otherwise,} \end{cases} \tag{9}$$

where $z^B = \frac{p/q}{1-\mu(p,q)}$ *is the equilibrium cut-off that defines the marginal lender-seller in an active securitization market and* $n(z^*)$ *is the lender's policy function consistent with the securitization equilibrium outcome.*

Comparative Statics. An important property of the model is that the information wedge endogenously widens as the default rate (λ) increases. Figure 3 compares the response of market aggregates between an economy with information frictions against an economy with complete information; it shows that the contraction of aggregate credit to changes in the default rate is amplified in the presence of information frictions.

Figure 3: Amplification of aggregates to credit default



Source: Authors elaboration. The figures compare aggregates in the simplified credit model with and without information frictions in securitization for different values of λ.

Figure 3 shows how information frictions may amplify the response of aggregates to changes in default risk; the left panel shows that as the fraction of defaulting loans in the economy increases, the volume of securities traded declines much more rapidly in the economy with information asymmetries. Security prices follow a similar pattern: high default risk results in a higher proportion of securitized low-quality loans, driving up the cost of purchasing securities and reducing demand. As a result, the price of securities that clears the market falls. Absent information frictions, low-quality loans are not traded, and the price of securities remains unaffected by default risk (central panel). The discontinuity observed in trading volume and security prices represents the threshold of default risk above which the securitization market becomes inactive. Due to the equilibrium connection between both markets, a lower securitization volume implies lower liquidity available for new lending in the credit market. Moreover, a shutdown of securitization may induce strong non-linear dynamics in lending volumes, amplifying the contraction of credit (right panel).

Up to this point, we have illustrated how information frictions in securitization can amplify the response of credit aggregates when default risk is high. In the quantitative section 4, we show that (i) in general equilibrium, a "financial accelerator" effect in the credit market arises once borrower's default is endogenously modelled[13]; (ii) the data on cross-sectional moments of mortgage lending is informative about the magnitude of the amplification of information frictions.

3 The Quantitative Model

This section outlines the quantitative model we take to the data.

Time is discrete and infinite. The model is an exchange economy with a continuum of lenders and a borrower household. Borrowers (B) discount the future more heavily than lenders (L), with $\beta^B < \beta^L$. The borrower household derives utility from housing services and non-durable consumption, with perfect risk-sharing across its members. Each period, it receives a stochastic income endowment and starts with an initial stock of housing and mortgage debt. Lenders, with log preferences over dividends, are initially endowed with ownership of the borrower household's mortgage debt.

The economy features three asset types traded in distinct markets. In the housing market, the borrower household buys and sells housing units, while lenders only sell foreclosed ones. In the credit market, borrowers and lenders exchange resources through long-term mortgage loans collateralized by the borrower's housing stock. The third asset is mortgage-backed securities (MBS), which bundle the mortgage loans lenders sell in the securitization market. Only lenders participate in the securitization market, with some selling legacy loans and others purchasing MBS.

Borrower household members experience housing depreciation shocks and prepayment shocks. As a family, they optimally decide to default, repay, and prepay their mortgage loans. Lenders face idiosyncratic stochastic loan-origination costs and, as creditors of the borrower's household, are exposed to default and prepayment risk on their mortgage portfolios. There is no recourse upon default; lenders bear the losses from foreclosing the housing collateral. A novel ingredient of the model is that lenders may also hold MBSs, so they may also face losses from the MBS holdings upon the borrower's default. In the securitization market, trading of loans and MBSs is affected by private information about loan's quality (probability of default) among lenders.

Government policy is modeled as a credit guarantee on MBSs that insures lenders who buy

[13] This mechanism is at the heart of our information frictions multiplier, and it is similar to Morris and Shin (2012)'s idea of *contagious adverse selection*, in which even small expected losses weaken *market confidence* and can lead to a complete disruption of trade in asset markets.

securities against losses from borrowers' default. The government balances its budget by charging lender-originating loans an origination fee and finances any deficit by taxing borrowers and lenders.

We now describe the borrower and lenders problems in detail.

3.1 Borrowers

We assume a family construct for the borrower household—as in Elenev et al. (2016) and Faria-e Castro (2022)—to model partial default in a tractable manner. Under this setup, the household is split into a continuum of members indexed by $i \in [0, 1]$. The household provides perfect consumption insurance against idiosyncratic shocks, so all members have the same allocations but differ only in their default decisions. At the beginning of every period, each member owns the same amount of housing stock h_t such that $\int_0^1 h_t di = H_t$ and the same stock of liabilities or mortgage debt b_t such that $\int_0^1 b_t di = B_t$.

Preferences and Endowments. The borrower household has preferences over a final numeraire consumption good C_t and over the housing services from owning a housing stock H_t given by

$$U(C_t, H_t) = (1 - \theta) \log C_t + \theta \log H_t,$$

where θ represents the valuation of housing services relative to other non-housing consumption goods. The household receives a stochastic income endowment Y_t every period. We assume income follows an autoregressive-process of first order and represents an exogenous aggregate state of the economy. In order to finance house purchases, the household takes on long-term debt (mortgages) extended by lenders. At each period t, the household begins with an outstanding stock of liabilities or mortgage debt B_t and a stock of housing H_t. Housing units are traded at price p_t^H.

Mortgages. Mortgages are modeled as long-term loans subject to default and prepayment. The loan contract is characterized by (δ, κ): $\delta \in (0, 1)$ represents the mortgage (inverse) duration, and $\kappa > 0$ the coupon payment on the outstanding principal $\kappa(1 - \delta)$.[14] New mortgage loans N_t are priced competitively at the discounted price q_t.

Default. Household members experience housing valuation shocks $\omega_t^i \sim G_\omega(\mu_\omega, \sigma_{\omega_t}^2)$, which scale the value of their housing holdings to $\omega_t^i p_t^H h_t$, with $\omega_t^i \in [0, \infty)$. The mean μ_ω is constant, while the standard deviation σ_{ω_t} fluctuates over time —serving as an exogenous aggregate state variable representing mortgage credit risk. Appendix B.1 shows that the default rate at the household level

[14]This contract structure reflects key features of 30-year fixed-rate mortgages in the U.S. Following Chatterjee and Eyigungor (2015); Elenev et al. (2016), we treat mortgages as perpetuities, so principal declines over time, and borrower equity builds steadily. A fixed duration δ avoids tracking loans of various vintages, simplifying state variables while capturing aggregate mortgage cash flow dynamics for lenders.

is characterized by a threshold $\bar{\omega}_t$—a function of endogenous and exogenous aggregate states, such that only members with $\omega_t^i \leq \bar{\omega}_t$ default on their mortgages. Given $\bar{\omega}_t$, the aggregate default rate is defined as $\lambda(\bar{\omega}_t) = Pr[\omega_t^i \leq \bar{\omega}_t]$.

Foreclosure. Upon borrowers' default, lenders foreclose the housing collateral. Foreclosure is costly, and foreclosed houses usually sell at a discount due to rapid liquidation by financial institutions (Campbell et al. (2011)). We assume lenders recover only a fraction $\psi \in [0, 1)$ of the market value. The recovery function, per-unit of debt, is given by $\Psi_t(\bar{\omega}_t) = \psi \mathbb{E}[\omega_t^i | \omega_t^i < \bar{\omega}_t] \frac{p_t^H H_t}{B_t}$, where the conditional expectation reflects the average quality of foreclosed houses across the household's members.

Prepayment. Following default decisions, a fraction $\eta_t \in [0, 1)$ of non-defaulting household members faces a prepayment shock, leading them to repay their full outstanding principal. To capture aggregate prepayment dynamics and macroeconomic factors, we model η_t as an exogenous process positively correlated with household income.[15] Given the mortgage contract structure, the effective amortization rate is $\phi_t = \delta(1 - \eta_t) + \eta_t$, representing the maturity rate per unit of debt after accounting for prepayments. Additionally, we can summarize mortgage payments, per unit of debt, by letting $m_t = \phi_t + \kappa(1 - \phi_t)$ denote total mortgage payments, comprising amortized principal and coupon payments.

Borrowers' Recursive Problem. The problem is defined by endogenous states $\{B_t, H_t\}$, and a vector of exogenous states X_t (to be defined later). The borrower household solves the following problem:

$$V^B(B_t, H_t; X_t) = \max_{\{C_t, N_t, H_{t+1}, \bar{\omega}_t\}} U(C_t, H_t) + \beta^B \mathbb{E}_{X_{t+1}|X_t} V^B(B_{t+1}, H_{t+1}; X_{t+1}), \tag{10}$$

subject to:

$$C_t + p_t^H H_{t+1} + \Xi_{H,t} + m_t(1 - \lambda(\bar{\omega}_t))B_t + T_t^B = (1 - \lambda(\bar{\omega}_t))\mu_\omega(\bar{\omega}_t) p_t^H H_t + q_t N_t + Y_t \tag{11}$$

$$B_{t+1} = (1 - \phi_t)(1 - \lambda(\bar{\omega}_t))B_t + N_t, \tag{12}$$

$$B_{t+1} \leq \pi p_t^H H_{t+1}, \tag{13}$$

where (11) is the the household's budget constraint. On the left side, expenses include consumption, housing purchases, and a moving cost $\Xi_{H,t} = p_t^H H_{t+1} \frac{\nu}{2} (\frac{p_{t+1}^H H_{t+1}}{p_t^H H_t} - 1)^2$— reflecting housing transaction costs (Piazzesi and Schneider (2016)), household's net mortgage payments net of defaults, and lump-sum taxes T_t^B. The right side of (11) represents income sources: the market value of housing

[15] Gabaix et al. (2007) show that mortgage prepayments correlate positively with consumption and income, while Chernov et al. (2017) find that prepayment risk-premia in MBS is tied to income, employment, and housing shocks.

holdings (where $\mu_\omega(\bar{\omega}_t) = \mathbb{E}[\omega_t^i | \omega_t^i \geq \bar{\omega}]$ reflects the value among members who avoid default), new mortgage credit $q_t N_t$, income endowment Y_t.

The law of motion for the stock of mortgage debt in (12) consists of two parts: the total outstanding mortgage debt net of default and newly originated mortgage loans. Default impacts household finances by reducing outstanding liabilities and mortgage payments, but it also lowers the aggregate housing stock. Additionally, the borrower household also faces a borrowing constraint (11); limiting end-of-period debt B_{t+1} to a fraction π of the next period's market value of housing stock. π reflects the loan-to-value (LTV) regulatory limit.

3.2 Lenders

Preferences and Endowments. Lenders are patient agents representing savers and financial companies that lend resources to borrowers. There is a unit mass of lenders, indexed by $j \in [0, 1]$, with a dividend smoothing function over the final consumption good given by:

$$u(c_t^j) = \log c_t^j.$$

Lenders are assumed to have limited access to debt markets and to operate only with private equity given by their ownership of the borrower's debt.[16] A lender j's stock of mortgage loans is denoted by b_t^j. We assume that each lender holds a diversified loan portfolio across household members such that each is equally exposed to their prepayment and default decisions (explained above).

Loan Origination Technology. As in Section 2, lenders are heterogeneous in their lending technology. At the start of each period t, lender j draws an idiosyncratic loan origination cost z_t^j, independently distributed across lenders and time, with $z_t^j \sim F(z)$ over $[\underline{z}, \bar{z}] \in \mathcal{R}^+$. Each lender originates new loans n_t^j at a linear cost of $n_t^j z_t^j$, representing private, idiosyncratic risk tied to underwriting, screening, and lending opportunities. This heterogeneity generates varying liquidity needs over time and motivates loan sales and security purchases in the securitization market (explained below).

Private Information. At the beginning of the period, each lender privately infers the fraction $x_{\ell t}^j \in [0, 1]$ of low-quality mortgages— those with low repayment prospects that are likely to default with probability ρ. For simplicity, we assume that high-quality mortgages (fraction $1 - x_{\ell t}^j$) repay with certainty.[17] This feature generates different expected cash flows according to the mortgage quality;

[16] Our setting focuses on capturing relevant features of a large fraction of mortgage originators with limited funding sources and acting as financially constrained intermediaries.

[17] In our setup, ρ can be interpreted as the result of the lender's credit risk screening capabilities. When $\rho = 1$, lenders perfectly identify likely defaults within their portfolios, replicating the setup in Section 2. For $\rho < 1$, defaults within the lender's portfolio are only partially predictable. See Vanasco (2017), Neuhann (2019), and Caramp (2019) for models focusing on borrower credit risk screening and originator moral hazard.

we denote the expected per-unit cash flow from low-quality mortgages as $m_{\ell t} = (1-\rho)m_t + \rho\Psi(\bar{\omega}_t)$, a function of mortgage payments and recovery from foreclosure. In contrast, high-quality mortgages pay $m_{ht} = m_t$. Lenders predict the aggregate default rate of the economy and use it to infer $x^j_{\ell t}$ according to the following relation:

$$\rho x^j_{\ell t} = \lambda(\bar{\omega}_t) \qquad \forall\ j, t, \tag{14}$$

which indicates that each lender's expected portfolio default rate aligns with the aggregate default rate, consistent with lenders diversifying across borrowers. The source of private information arises from a lender's capacity to privately identify a mortgage's quality at the beginning of each period, and it captures the observation that ex-ante, a lender can better predict and identify high- and low-quality loans within her portfolio but does not know with certainty which loans will default.[18] An outsider cannot make such a distinction. At the time of sale, all mortgages—both high and low-quality—are current and in good standing. By the end of the period, after the household's default rate is determined in equilibrium, mortgages are publicly identifiable as either performing or non-performing.

Trading in the Securitization Market. Lenders participate in a securitization market a la Kurlat (2013), where they can buy securities and sell their legacy loans at a pooling price p_t. Each lender j makes trading decisions $\{s^j_{ht}, s^j_{\ell t}, d^j_t\}$ where s^j_{ht} and $s^j_{\ell t}$ represents sales of high- and low-quality loans, respectively, and d^j_t denotes security purchases.

Similar to the stylized model in Section 2, lenders' private information about the quality of their legacy loans generates incentives to selectively sell low-quality loans first, leading to a classic adverse selection problem.[19] Using the notation from our stylized model, let μ_t denote the fraction of low-quality loans sold into securitization affected by borrowers default:

$$\mu_t = \frac{\rho S_{\ell t}}{S_t}, \tag{15}$$

[18]Private information about loan quality, leading to asymmetries between loan originators and MBS buyers, often arises during borrowers' screening. For example, originators may have *soft* information on credit quality (Keys et al., 2010; Demiroglu and James, 2012) or observe borrower misreporting (Jiang et al., 2014) or choose to misrepresent borrowers' characteristics (Piskorski et al., 2015b). Even when both parties observe the same data, originators may have superior information than MBS buyers by developing better valuation models (Shimer, 2014; Krainer and Laderman, 2014).

[19]Modeling adverse selection in the securitization market reduces trade volume when borrowers' credit risk rises, or housing collateral values decline—a pattern consistent with the data. In our pooling market, adverse selection persists across periods because a lender's type (origination cost) is privately observed and i.i.d. over time, preventing traders from distinguishing liquidity-driven loan sales from strategic ones (offloading low-quality loans). Chari et al. (2014) show that pooling equilibria with persistent adverse selection can arise even when lender types are persistent and there is learning from trading (reputational dynamics).

where $S_{\ell t}$ is the aggregate supply of low-quality loans, S_{ht} denotes the aggregate supply of high-quality loans, and $S_t = S_{ht} + S_{\ell t}$ the aggregate supply of all loans traded.

The securitization process pools all loans sold into the market to create representative mortgage-backed securities. Since all loans in the bundle share the same coupon and maturity structure, securities can seamlessly accumulate in lender-buyers' portfolios. The law of motion of a lender's loan portfolio is given by:

$$b^j_{t+1} \quad = \quad n^j_t + (1-\phi_t)\left((1-x^j_{\ell t})b^j_t - s^j_{ht} + (x^j_{\ell t}b^j_t - s^j_{\ell t})(1-\rho) + (1-\mu_t)d^j_t\right), \tag{16}$$

where the next period's portfolio includes newly originated loans n^j_t, non-maturing mortgages remaining after securitization of high- and low-quality loans, and net security purchases $(1-\mu)d^j_t$. The term $(1-\mu)$ acknowledges that fraction μ of all traded mortgages is liquidated due to borrower defaults.

Government policy. We capture U.S. government policy in the securitization market with two instruments.[20] First, we let the cash flow of an insured MBS equal that of high-quality mortgages, $m_{gt} = m_{ht}$, shielding buyers from default risk while leaving them exposed to prepayment risk only. Second, a subsidy $\tau_t(\mu_t)$ is applied to MBS prices, reflecting government incentives to maintain market liquidity. We make the subsidy an endogenous function of μ_t to capture the contingent character of credit guarantees. To fund this policy, the government charges a credit guarantee fee γ_t to loan originators (lenders) and balances any deficit through lump-sum taxes on the borrower household and all lenders.

Recursive Problem of a Lender. The set of individual endogenous states that characterize the problem of a lender j is $\{b^j_t, z^j_t\}$. The variable X_t denotes the same set of aggregate exogenous states faced by the borrower household. The recursive representation is as follows:

$$V(b^j_t, z^j_t; X_t) \quad = \quad \max u(c^j_t) + \beta^L \mathbb{E}_{X_{t+1}|X_t} V(b^j_{t+1}, z^j_{t+1}; X_{t+1}) \tag{17}$$

A lender's recursive problem consists of choosing policy functions $\{c^j_t, b^j_{t+1}, d^j_t, s^j_{ht}, s^j_{\ell t}\}$ to maximize (17) subject to the law of motion of their legacy portfolio in (16) and subject to:

$$\begin{aligned} c^j_t + &n^j_t(z^j_t q_t + \gamma_t) + p_t(1-\tau_t)d^j_t \\ &\leq ((1-x^j_{\ell t})b^j_t - s^j_{ht})m_{ht} + (x^j_{\ell t}b^j_t - s^j_{\ell t})m_{\ell t} + p_t(s^j_{ht} + s^j_{\ell t}) + d^j_t m_{gt} - T^L_t b^j_t, \end{aligned} \tag{18}$$

$$s^j_{ht} \in [0,\ (1-x^j_{\ell t})b^j_t], \tag{19}$$

$$s^j_{\ell t} \in [0,\ x^j_{\ell t}b^j_t]. \tag{20}$$

[20] In the U.S., government-sponsored enterprises (GSEs) such as Freddie Mac and Fannie Mae dominate the MBS market, accounting for over 95% of its activity. These GSEs provide a credit guarantee to MBS buyers (security cash flows are insured against default risk on the underlying mortgages) and finance this insurance by charging mortgage originators a guarantee fee.

The flow of funds constraint in (18) outlines lender j's outflows on the left-hand side: dividend payments, new loan originations issued with idiosyncratic cost z_t^j, at discounted loan price q_t, and considering the per-unit guarantee fee γ_t.[21] Additionally, $p_t d_t^j$ reflects security purchases adjusted for the MBS subsidy τ_t. The right-hand side lists funding sources: cash inflows from retained maturing high- and low-quality loans, proceeds from loan sales $p_t(s_{ht}^j + s_{\ell t}^j)$,[22] cash flows $d_t^j m_{gt}$ from MBSs purchases bearing government guarantees, and proportional taxes. (19) and (20) represent portfolio restrictions over sales of high- and low-quality loans. It is assumed that new loans and security purchases are non-negative, $n_t^j \geq 0$ and $d_t^j \geq 0$.

3.3 Markets Clearing

State Variables The set $X_t = \{Y_t, \eta_t, \Gamma_t(b, z), \sigma_{\omega t}, B_t, H_t\}$ represents aggregate states of the economy. Here, $\{Y_t, \eta_t, \sigma_{\omega t}\}$ are exogenous states: the borrower household's income endowment, the household's prepayment shock, and the volatility of the housing valuation shocks, respectively. These exogenous shocks follow Markov processes, see appendix D.3 for estimation details. $\Gamma_t(b, z)$ represents the joint cumulative distribution of lenders over the loan stocks and origination costs.[23] B_t and H_t are the aggregate stock of loans and the aggregate stock of housing in the economy, respectively.

The housing market is in fixed supply, so in equilibrium:

$$H_{t+1} = \bar{H}. \tag{21}$$

Market clearing in the credit market requires the aggregate lending supply to meet the lending demand from the borrower household:

$$N_t = \int n_t^j \; d\Gamma_t(b, z). \tag{22}$$

Whenever the securitization market is active, the market clearing condition:

$$S_t \geq D_t, \tag{23}$$

holds with equality. Recall that S_t denotes the aggregate supply of loans sold for securitization, $S_t = S_{ht} + S_{\ell t} \equiv \int s_{ht}^j \; d\Gamma_t(b, z) + \int s_{\ell t}^j \; d\Gamma_t(b, z)$. The demand of securities is $D_t = \int d_t^j \; d\Gamma_t(b, z)$.

The government budget constraint is given by

$$\gamma_t N_t + T_t^B + T_t^L B_t = \tau_t p_t D_t + \mu(m_{ht} - \psi(\bar{\omega}_t)), \tag{24}$$

[21] The guarantee fee is typically a surcharge, in basis points, to the borrower's loan interest rate, expressed here in units of q_t. See Appendix D for details.

[22] In section 2, we showed that lenders first sell low-quality loans at any positive security price. When low-quality loans feature collateral recovery value $\Psi(\bar{\omega}) > 0$, this holds if $p > \Psi(\bar{\omega})$.

[23] Since z^j is iid, it is independent of b^j, making Γ the product of the cumulative distribution function F for the origination cost and an unspecified cdf for b.

where on the left-hand side, $\gamma_t N_t$ represents government revenue from the guarantee fee, while T_t^B and $T_t^L B_t$ denote the lump-sum tax on borrowers and the proportional tax on lenders, respectively. The right-hand side comprises government expenditures from the subsidy to security buyers and from guaranteeing MBS cash flows.

The aggregate resource constraint is given by

$$C_t + \int c_t^j d\Gamma_t(b,z) + I_t^H + \Xi_{H,t} + \zeta_t \leq Y_t, \tag{25}$$

where I_t^H denotes housing investment, $\Xi_{H,t}$ are the borrower housing adjustment costs, and $\zeta_t = q_t \int (z_t^j - 1) n_t^j \, d\Gamma_t(b,z)$ captures the aggregate cost of lending in the economy, requiring aggregation across lenders originating loans.

3.4 Competitive Equilibrium

A recursive competitive equilibrium[24] given government policy $\{\gamma, \tau, T^B, T^L\}$ consists of value function $V^B(B, H; X)$ and policy functions for the borrower household $\{C, N, H', \bar{\omega}\}$, value functions $V(b^j, z^j; X)$ and policy functions $\{c^j, b'^j, d^j, s_h^j, s_\ell^j\}$ for lenders $j \in J$, aggregate law of motion for the joint distribution of loans and origination costs $\Gamma'(b,z)$, the fraction of securitized low-quality loans $\{\mu\}$, and price functions $\{q, p, p^H\}$ such that: (i) borrowers' value function and policy functions solve the problem in (10), taking $\{q, p, p^H\}$ as given; (ii) lenders' value functions and policy functions solve the problem in (17), taking $\{q, p, \mu\}$ as given; (iii) the housing price p^H clears the housing market: (21); (iv) the discounted price of lending $q > 0$ clears the credit market: (22); (v) whenever the securitization market is active, there is an equilibrium price p that clears the securitization market (23) and the fraction of securitized low-quality loans μ is given by (15); (vi)the aggregate fraction of non-performing low-quality loans in the economy equals the aggregate household's default in (14); (vii) the aggregate law of motion for $\Gamma'(b,z)$ is generated by the Markov processes of the exogenous states, the distribution of lenders' origination costs $F(z)$, and consistent with lenders' policy functions b'^j; (viii) the government budget constraint (24) is satisfied every period; (ix) the resource constraint (25) holds every period.

4 Quantitative Analysis

4.1 Calibration and Estimation

The model is calibrated at an annual frequency for the period 1990–2018. Table 1 summarizes the parameters and the data targets.

Borrower Preferences and Housing. The borrower's discount factor, β^B, is set to 0.97 to match the consumption-to-disposable income ratio of 0.79 based on NIPA data, including consumption of

[24] Time indexing is suppressed for variables in t, and variables in $t+1$ are indicated by the superscript $'$.

non-durables and services. The time discount factor for lenders, $\beta^L = 0.984$, is calibrated to match the average real rate of 1-year Treasury bills. The housing preference parameter $\theta = 0.22$ is set to match the new residential mortgage credit-to-residential real estate ratio of 0.14, as reported in the U.S. Financial Accounts. The parameter ν is calibrated to 3.5, corresponding to a 6% moving transaction cost relative to the housing market value (Piazzesi and Schneider (2016)). The loan-to-value ratio, $\pi = 0.80$, reflects the average LTV on first-lien mortgages across all originators from the NMDB. The mean of borrowers' housing valuation shocks, $\mu_\omega = 0.971$, is chosen to match the 2.91% average depreciation rate of private residential capital, as reported by the BEA.

Mortgages and Prepayment. We model 30-year fixed-rate mortgages (FRMs) with a fixed duration parameter, $\delta = 0.03$, and a coupon rate, $\kappa = 0.05$. The prepayment rate, η_t, is modeled as a function of an exogenous disturbance, ϵ_η, which correlates positively with household income, reflecting that households are more likely to prepay mortgages during favorable macroeconomic conditions (Gabaix et al. (2007); see Appendix D.3). The mean prepayment rate of the process, $\bar{\eta} = 0.12$, and its standard deviation 0.03, are consistent with historical prepayments for conventional 30-year FRMs as reported by Fannie Mae and Freddie Mac. The maturity structure and prepayment dynamics imply an effective duration of 7.25 years for the model's mortgage bond, in line with empirical estimates (Walentin (2014)).

Housing and Income risk. The cross-sectional variance of housing valuation shocks, $\sigma^2_{\omega,t}$, is modeled as a first-order Markov process with two regimes. Using FHFA house price index data for all 51 U.S. states from 1975 to 2020, we estimate a first-order Markov process for the variance of house price growth, distinguishing between low- and high-volatility regimes.[25] For the low-volatility regime, the estimated state space, combined with income and prepayment processes, replicates an untargeted default rate of 0.98% in normal times. In contrast, the high-volatility regime underestimates default rates observed during the foreclosure crisis. To address this, we calibrate the two highest housing valuation shock states to match a default rate of 4.35% during crisis periods and an unconditional default rate of 2.04%, consistent with the national 90-days-or-more delinquency rate reported by the NMDB (see Table 2).[26]

We model borrower household income, Y, using the HP-filtered cyclical component of Gross Domestic Product (GDP). Following Elenev et al. (2016), we combine the processes for the variance of housing valuation and the borrower's income into a joint first-order Markov process. This approach replicates a recession probability of 0.34, in line with the long-term NBER frequency of recessions. In

[25]See Appendix D.3 for details. This approach builds on Elenev et al. (2016), who model $\sigma^2_{\omega,t}$ as a Markov process to capture exogenous forces driving mortgage credit risk during the 2007–2012 foreclosure crisis. Unlike their work, we use publicly available house price index data to estimate the underlying process.

[26]The delinquency rate includes mortgages 90 days or more past due, in foreclosure, or linked to bankruptcy as of year-end.

our framework, mortgage crises are recessions characterized by negative income shocks and elevated housing risk, triggering default waves similar to those observed in the data. The probability of a mortgage crisis is 0.082, consistent with Jordà et al. (2013) and Jordà et al. (2016), who find that about one in four recessions in advanced economies are driven by mortgage-related financial crises.

Table 1: Calibration for the benchmark economy

	Description	**Value**	**Source/Target**
	Borrowers		
β^B	Borrowers discount factor	0.97	Consumption to disposable income. 90-18.
θ	Housing expenditure share	0.22	Mortgage credit to residential real estate. 90-18.
π	Loan to value ratio	0.80	Loan to value at origination. FHFA 90-18.
ν	Housing adjustment costs	3.50	Piazzesi and Schneider (2016)
μ_ω	Mean housing valuation	0.97	Residential capital depreciation (BEA).
$\sigma^2_{\omega^H}$	Variance of housing shocks	$\{0.006, 0.009\}$	Mortgage default rate in crisis times, 09-13. NMDB
	Mortgages		
δ	Mortgage contract maturity	0.03	Standard for 30y FRM
κ	Mortgage contract coupon	0.05	Standard for 30y FRM
$\bar{\eta}$	Prepayment rate, mean.	0.12	Mean prepayment, conv. 30-yr FRM. SIFMA.
ϵ_η	prepayment rate, std	0.03	Std prepayment, conv. 30-yr FRM. SIFMA.
ψ	Foreclosure recovery	$\{0.50, 0.65\}$	Mortgage severities (Appendix).
	Lenders		
β^L	Lenders discount factor	0.984	Mean 1y Tbill real rate.
lc	Location of origination dist.	0.694	Estimated Appendix D.
s_1	Shape origination dist.	7.55	Estimated Appendix D.
s_2	Shape origination dist.	5.95	Estimated Appendix D.
ρ	Prob. default low-quality	0.82	Mean fraction of securitized loans. HMDA 90-18.
	Government		
γ	Guarantee fee	20 bps	Mean GSEs guarantee fee, 90-06.
α	Securities subsidy coverage	0.60	Market share of agency RMBS, 90-06.

Housing Foreclosure. We set the foreclosure recovery fraction, ψ, to 0.65 in normal times and 0.50 in crises to reflect lenders' liquidation costs. These recovery rates, combined with housing valuation shocks, produce loss-given-default (severity) rates of 34.6% in normal times and 49.8% during crises, consistent with observed rates for loans with 80% LTV, as reported by Fannie Mae and Freddie Mac, and with values in the literature (Campbell et al. (2011)). Combining severity with default rates results in net-loss rates of 0.8% and 2.2% for lenders in normal and crisis times, respectively. While ρ, the probability of default on low-quality loans, lacks a direct data counterpart, we set it to 0.82 to match the average fraction of loans sold into securitization (0.70) by large originators from 1990 to 2018, according to HMDA.

Lenders Technology. We model the distribution of origination costs across lenders, $F(z)$, as a generalized beta distribution with shape parameters (s_1, s_2). Since no direct data counterpart exists, we estimate the parameters of $F(z)$ using the simulated method of moments (SMM), targeting the market share of the third and fourth quartiles of the mortgage lending distribution. These moments are derived from the HMDA panel of mortgage originators, covering 1990–2018.[27] The distribution's support is normalized by setting the scale $sc = \bar{z} - \underline{z}$ to 1, and the location parameter $lc = \underline{z}$ to match the mortgage spread to the 10-year Treasury bill from 1990 to 2018. The non-targeted moments in Table 2 show that the model also fits well other moments of the cross sectional distribution of lending.

Government Policy. The government's policy instruments are γ, τ. In the benchmark economy, we calibrate the credit guarantee fee, γ, to 20 basis points, reflecting the average fee charged by Fannie Mae and Freddie Mac before the GFC.[28]. For the coverage of credit guarantees, we calibrate the benchmark economy to a partially insured securitization market, consistent with the pre-GFC period (1990–2006), when private securitization played a significant role. Specifically, we set $\tau_t = \alpha\mu_t$, where $\alpha \in [0, 1]$ represents the government's coverage of credit guarantees, and μ_t is the endogenous function given by (15). When $\alpha = 1$, the policy fully offsets a security buyer's losses from mortgage defaults, i.e., $\tau_t = \mu_t$ represents a credit guarantee as provided by the GSEs. Conversely, when $\alpha = 0$, security buyers fully bear the losses from households' default, with $\tau_t = 0$. In the benchmark economy, we set $\alpha = 0.6$, consistent with the pre-GFC market share of GSE securitization.[29] In Section 4.4, where we examine the post-GFC economy, we set $\alpha = 1$ to explore the dynamics of the current securitization market. In the benchmark economy, any deficit from the credit guarantee scheme is financed through lump-sum taxes, equally levied on borrowers and lenders. For the post-GFC analysis, we relax this assumption and compute the break-even credit guarantee fee that eliminates the deficit.

Non-targeted moments. The model fits the data well, with targeted and non-targeted moments closely matching their data counterparts. The second part of Table 2 shows that the model generates a high, positive correlation between the volume of credit and securitization, consistent with the data.

[27]See Table 8 in Appendix D.1. The HMDA dataset mandates mortgage originators to disclose information on loan applications, originations, and purchases.

[28]See Appendix D.3 for the expression of γ as a function of the quoted credit guarantee in basis points.

[29]We focus on the aggregate securitization market, without modeling market segmentation explicitly. Post-GFC, the non-GSEs segment has shrunk to less than 5% of total RMBS issuance, see Appendix D.1.

Table 2: Targeted and Non-targeted Moments

Targeted Moments

Variable	Model	Data	Description
Borrowers			
Consumption to income	0.80	0.80	Consumption to disposable income, NIPA 90-010.
Mortgage to housing stock	0.14	0.15	New mortgage lending to residential real estate. 90-18.
Mortgage spread (pp)	1.74	1.66	Spread w.r.t 10y Tbill, 90-18.
Default rate - uncond. (pp)	2.04	2.01	Mortg. delinquency (90d + foreclosure). NMDB, 91-18.
Default rate - crisis (pp)	4.35	4.05	Mortg. delinquency (90d + foreclosure). NMDB, 07-12.
Lenders			
Fraction of loans securitized	0.70	0.70	Mortgages securitized within 1st-year. HMDA 90-18.
Severity rate - uncond. (pp)	34.6	32.2	Mean severity, mortgages w/ LTV 60-80. GSEs 99-17.
Severity rate - crisis (pp)	49.8	43.9	Mean severity, mortgages w/ LTV 60-80. GSEs 05-08.
Market share Q4	0.958	0.961	Distribution of mortgage lending (Q4). HMDA, 90-18
Market shares Q3	0.040	0.029	Distribution of mortgage lending (Q3). HMDA, 90-18.

Non-targeted Moments

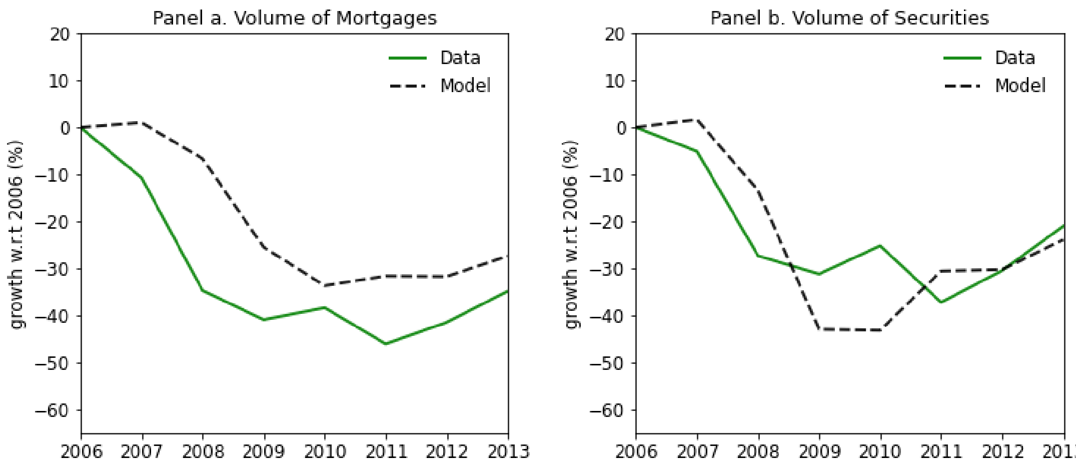
Variable	Model	Data	Description
Default normal-times (pp)	0.98	1.20	Mortg. deliquency (90d + foreclosure). NMDB, 90-06.
Mortg. effective duration	7.25	7.50	Effective duration of 30y FRM. Walentin (2014)
Market shares Q1	0.000	0.002	Cross-section mortgage lenders. HMDA, 90-18.
Market shares Q2	0.002	0.008	Cross-section mortgage lenders. HMDA, 90-18.
Fraction of small lenders	0.84	0.91	Cross-section mortgage lenders. HMDA, 90-18.
Correlations			
Volume security w/ lending	0.92	0.98	RMBS issuance and mortgage lending (HDMA).
Default w/ lending growth	-0.17	-0.35	Mortgage delinquency and mortgage lending growth.
Default w/ mortg. spread	0.90	0.53	Mortgage delinquency and mortgage spread.

This correlation arises from the endogenous liquidity securitization channel embedded in the model. Other correlations of interest are the negative correlation between household default and the growth rate of mortgage lending and the positive correlation between household default and the mortgage spread, both of which align with the data.

4.2 An application to the Global Financial Crises

This section examines the model's predictions for aggregate outcomes in the mortgage market following the GFC. We start by asking: how much of the observed contraction in residential mortgage credit can be accounted for by disruptions in the securitization market? To address this question, we simulate the model under its benchmark calibration, using a sequence of aggregate household income and housing valuation shocks that replicates the observed path of GDP and default rates from 2006 to 2013, as shown in Figure 13 in Appendix D.2.

Figure 4: The mortgage market during the Global Financial Crisis



Authors elaboration. Panel a: Data, represented by the solid green line, shows the growth rate of aggregate new mortgage issuance (in USD) from HMDA. The Model simulation, represented by the black dashed line, shows the growth rate of new mortgage lending in the benchmark economy. Panel b: Data represents the growth rate of residential mortgage-backed securities (RMBS) issuance (in USD) from SIFMA. The Model corresponds to the growth rate of the securitization volume in the benchmark economy. All variables are expressed as two-year moving average growth rates relative to 2006.

The model accounts for two-thirds of the 40.6 percent contraction in aggregate residential mortgage lending observed from 2008 to 2013. Figure 4 shows the percentage changes in the volume of new mortgage lending and the volume of issuance of MBS (right panel) relative to 2006.

The model's success in generating large fluctuations rests on two factors. First, an endogenous information frictions multiplier amplifies the impact of household shocks. In the model, income and housing shocks induce fluctuations in household default rates, triggering shifts in the composition of lenders—sellers, holders, and buyers— and leading to significant aggregate credit fluctuations. This dynamic is further amplified in general equilibrium as household balance sheets respond to changes in credit conditions.

Starting in 2007, the data shows a sharp decline in household income, and a surge in mortgage defaults. In the model, rising defaults lower the average quality of securitized loans. This deterioration reduces securitization volumes and liquidity for mortgage originators. As a result, the volume of new mortgage lending contracts sharply. The contraction occurs because low-cost lenders, responsible for originating a significant share of new mortgages, reduce their reliance on securitization, shifting from securitizing their entire portfolios to securitizing only a small fraction. As in the stylized model of Section 2, the composition of mortgage originators changes, with fewer lender-sellers and more lender-holders emerging as the securitization market becomes less liquid. Since lenders rely on securitization to fund new mortgage issuance, this decline in market liquidity spillover to aggregate credit. Furthermore, the growing share of higher-cost lenders raises intermediation costs, driving up mortgage rates. These supply-side forces adversely impact household balance sheets, reducing access to mortgage credit, exacerbating defaults, and decreasing consumption.

Second, the characteristics of the cross-sectional distribution of mortgage lending play a key role in informing the degree of amplification. The estimated density of lenders' origination costs, $F(z)$, features a small mass of low-cost lenders and a large mass of high-cost lenders, consistent with the observed market structure where a small number of lenders account for a large share of lending. This structural feature of the U.S. mortgage market influences equilibrium prices and quantities, highlighting the substantial liquidity benefits of securitization. It also stresses mortgage originators' high reliance on securitization for funding, particularly among mortgage companies and large banks, as documented by Loutskina and Strahan (2009), Stanton et al. (2014), and Jiang et al. (2020).

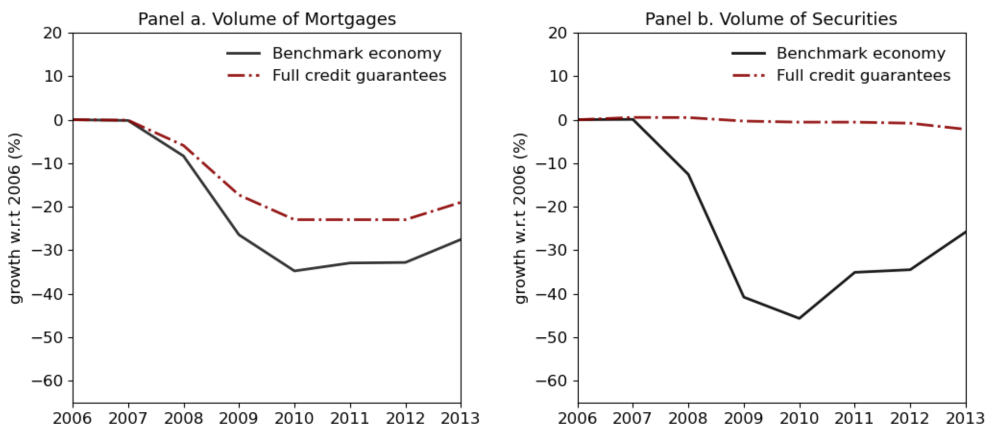
In the securitization market, the aggregate volume of MBS issuance declined by an average of 30%, while the model predicts a slightly larger average decline of 32.5% (see Panel b in Figure 4). However, the model overestimates the contraction in 2009 and 2010, primarily because it does not account for the large-scale asset purchase programs conducted by the Federal Reserve and Treasury Department during this period.[30] Naturally, as the model ignores these events, it predicts a stronger decline in security issuance. The model predictions for other household aggregates: house price growth, the mortgage spread, and aggregate consumption of non-durable goods are also in line with the observed dynamics in the data during this period (see Figure 14 in Appendix E).

Although aggregate MBS issuance contracted during this period, the performance of different securitization segments varied significantly. Government interventions allowed GSE securitization to continue with little disruption.[31] In contrast, private (non-GSE) securitization collapsed entirely, as shown in Figure 1 in section 1.1. While our model does not explicitly account for market segmentation, its predictions align with aggregate market dynamics, given the significant pre-GFC investor exposure to mortgage defaults via private securitization. Figure 5 examines the aggregate credit and securitization dynamics in a fully credit-guaranteed market resembling the GSE segment. Here, credit contraction is less pronounced than in the benchmark economy, and securitization ex-

[30] These interventions, initiated in September 2008, included \$1.25 trillion in MBS purchases by the Federal Reserve and \$221 billion by the Treasury to stabilize the mortgage market. At the same time, as part of a broader stabilization effort, Freddie Mac and Fannie Mae were placed into conservatorship by the FHFA.

[31] Fannie Mae and Freddie Mac incurred substantial credit losses during the financial crisis, and their securitization activities would likely have been severely impacted without the conservatorship intervention. See Frame et al. (2015) for details on the GSEs' financial position during this period.

Figure 5: Economies with full and partial credit guarantee



Panel a: *Benchmark* corresponds to the benchmark economy with partial credit guarantees, $\alpha = 0.6$. *Full credit guarantees* corresponds to post-GFC economy with $\alpha = 1$. All variables are expressed in growth rate with respect to 2006 with a two year moving average window. Both economies are simulated for the same sequence of shocks of income and housing volatility as explain in the Quantitative Section.

hibits a muted response to rising mortgage defaults. These dynamics align with the behavior of the GSEs-dominated market, where investors faced limited household credit risk exposure.

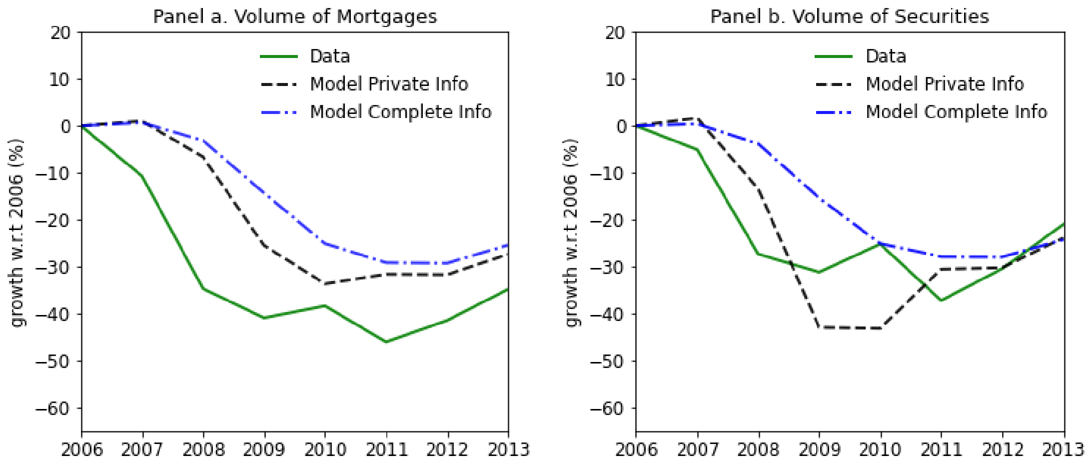
4.3 Quantifying Information Frictions

This section addresses two follow-up questions: Which shocks explain the observed behavior of the mortgage and securitization markets, and to what extent did information frictions amplify these shocks? To isolate the role of information frictions in amplifying household income and housing valuation shocks, we compare simulations of the baseline model to a counterfactual economy unaffected by information frictions— labeled the "complete information economy" (see Appendix F for details). In this counterfactual, lenders face the same government policies, liquidity frictions, and an exogenous distortionary wedge (similar to a tax on security purchases) that impacts their lending and trading decisions, but there is no adverse selection in securitization. Both economies are calibrated identically, ensuring comparability in their steady states. We repeat the simulation using the same income and housing volatility shock sequences observed during the GFC bust phase. Figure 6 presents the simulations for both economies and Table 3 shows their implied average contraction in the volumes of mortgage credit and securitization from 2008 to 2013.

Information frictions played an essential role in amplifying household shocks during the bust phase of the GFC. We estimate that information frictions amplified the mortgage credit contraction by a factor of 1.2 to 1.3 compared to an economy without such frictions in the securitization market. [32] The multiplier is the ratio of the average contraction in aggregates predicted by the baseline

[32] Large amplification effects from the securitization liquidity channel have also been documented at the micro level.

Figure 6: Quantifying Information Frictions During the Global Financial Crisis



Source: Model-simulated data. Panel a: *Data* is the aggregate volume of new mortgage issuance in U.S. dollar amounts. Source: HMDA database. Panel b. *Data* correspond to the volume of Residential Mortgage-backed security issuance U.S. dollar amounts. Source: SIFMA database. *Model Private Info* corresponds to the benchmark economy with private information. *Model Complete Info* corresponds to comparable model with complete information. All variables are expressed in growth rate with respect to 2006.

Table 3: Performance of the Baseline and the Counterfactual Economies, 2008-13

Aggregates	Baseline Economy	Counterfactual Economy	Data
Volume of Mortgages	-28.2	-22.9	-40.6
Volume of Securities	-32.5	-22.5	-29.8

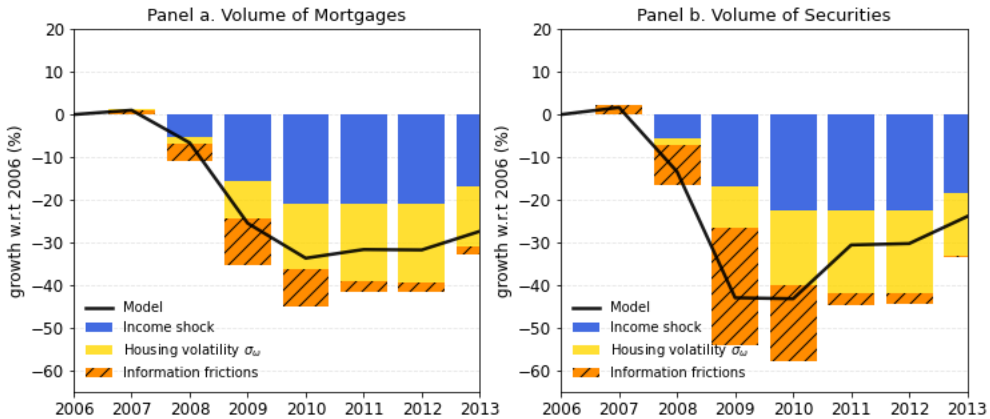
Source: Model-simulated data. Columns show the average contraction in aggregates for: the baseline economy with information frictions, the counterfactual economy without information frictions, and the data, covering the period from 2008 to 2013.

economy to that of the counterfactual economy from 2008 to 2013 (see Table 3).

Shock Decomposition. We now identify the contribution of household shocks to the observed dynamics of mortgage credit and securitization. Figure 7 presents a decomposition of these shocks. To compute each contribution, we first simulate the counterfactual complete information economy, introducing one shock at a time while keeping others at their unconditional means. The blue bars represent the impact of income shocks, and the yellow bars capture the effect of housing volatility shocks. Next, we estimate the role of information frictions by comparing the aggregate responses between the baseline and counterfactual economies. Due to the model's strong nonlinearities, the individual contributions do not sum to the total combined effect of all shocks, represented by the continuous black line.

Calem et al. (2013) find that the contraction in mortgage credit for commercial banks highly exposed to securitization liquidity was six times greater than for similar banks not dependent on securitization during the collapse of the private RMBS market.

Figure 7: Shock Decomposition during the Global Financial Crisis



Model-simulated data. The solid line shows the predicted contraction of the baseline model for income and housing shocks. Each bar represents the contribution of a shock. Solid blue bars represent the contribution of income shocks, yellow bars represent housing valuation shocks, and shaded orange bars illustrate the impact of information frictions.

Figure 7 shows that information frictions amplified household shocks most strongly from 2008 to 2010, coinciding with the unexpected surge in mortgage defaults. Although default rates remained historically high beyond 2010, the model predicts only a minor amplification effect from 2011 to 2013. These findings align with broader models examining the aggregate amplification effects of information frictions in asset markets through liquidity channels (e.g., Krishnamurthy, 2010; Kurlat, 2013; Bigio, 2015; Asriyan, 2020).

4.4 Evaluating the Current Securitization Market

The Post-GFC Economy. After the GFC, two significant changes reshaped the mortgage securitization market. First, the private securitization segment collapsed, leaving only the GSEs segment in place from 2008 onward. To reflect this structural shift, we set $\alpha = 1$, modeling a fully guaranteed GSEs-dominated market. Second, the guarantee fee (γ) charged by GSEs to mortgage originators increased significantly. Beginning in 2012, this fee rose from 20 to 60 basis points on average to align the price of credit guarantees more closely with private market pricing of mortgage credit risk.[33] We incorporate these two policy changes into the model and refer to this version as the post-GFC economy. Additionally, we use the model to calculate the break-even guarantee fee, defined as the fee level required to generate sufficient revenue to fund the credit guarantee policy without incurring a deficit. Table 7 presents selected statistics from the model's simulations for three scenarios: the base-

[33]Starting in 2011, the FHFA instructed GSEs to raise guarantee fees several times. For instance, an August 2012 FHFA press release stated: "These changes will move Fannie Mae and Freddie Mac pricing closer to the level one might expect to see if mortgage credit risk was borne solely by private capital. Figure 11 in Appendix D.1 documents the evolution of the guarantee fees.

line economy, the post-GFC economy, and an alternative post-GFC economy with the break-even guarantee fee.

The model predicts that the mortgage spread in the post-GFC economy settles slightly above its initial level in the baseline economy. This outcome is driven by two opposing forces: the higher guarantee fee pushes mortgage rates upward, while the increased guarantee coverage ($\alpha = 1$) lowers intermediation costs by easing lenders' trading costs in the securitization market. This dynamic aligns with observed patterns in the mortgage spread, as documented in Appendix D.1, comparing the periods 1990–2006 and 2013–2018. The post-GFC economy also exhibits greater mortgage spread volatility compared to the pre-GFC baseline. This arises because lower mortgage rates incentivize borrowers to consume more housing, increasing their stock of mortgage debt and leverage. As a result, equilibrium outcomes feature higher mortgage severity and default rates relative to the pre-GFC economy.

In the securitization market, security price volatility increases alongside mortgage spreads. This occurs because security prices continue to fluctuate due to general equilibrium effects driven by borrowers' credit demand. A fully guaranteed securitization market encourages more lenders to trade—either by purchasing securities or securitizing their entire portfolio—resulting in a higher average fraction of securitized loans in the post-GFC economy. This prediction also aligns with observed data for the post-GFC period. The information friction multiplier weakens significantly, reducing the probability of market collapse from 11.9% in the benchmark economy to just 0.51% in the post-GFC economy.

Pricing Credit Guarantees. Over the past decade, a key policy focus has been ensuring that GSEs credit guarantees accurately reflect household credit risk and fully cover the associated costs. Our model shows that while the price of credit guarantees tripled in the post-GFC economy, leading to higher revenues, the expansionary coverage of credit guarantees significantly increased expenses. As a result, the model predicts a larger deficit under the post-GFC policy compared to the baseline economy, indicating that credit guarantees may remain underpriced.

We estimate a break-even guarantee fee of 145 basis points for the post-GFC economy. Such an estimate incorporates the amplification effects of information frictions, which we argue are essential to account for the U.S. mortgage market's aggregate mortgage credit and securitization dynamics.[34] Column 3 of Table 4 presents the simulated moments for the post-GFC economy with the break-even guarantee fee. Notable differences arise when comparing the post-GFC economy (column 2) with the economy featuring the break-even guarantee fee. In the latter, mortgage rates increase

[34]Our result aligns with other studies on GSE credit guarantee policies. Elenev et al. (2016) also find that credit guarantees were underpriced in the pre-GFC period and may still be underpriced post-GFC. They note that the price fails to reflect the aggregate costs of banks' excessive leverage (moral hazard) when the government provides both deposit insurance and mortgage guarantees.

Table 4: Comparing Economies after the Global Financial Crisis

Description	Benchmark	Post-GFC	Post GFC + break-even fee
Borrower Household			
Consumption, ΔC	-	-5.06	-0.87
Mortgage debt, ΔB	-	11.8	5.59
Default rate - uncond.	2.04	2.79	1.87
Default rate - crisis	4.35	5.86	3.99
Credit Market			
Credit Guarantee fee (bps)	20	60	150
Mortgage spread, mean	1.74	1.85	1.59
Mortgage spread, std	0.76	1.19	1.12
Mortgage loss rates - crisis	2.17	2.98	2.00
Securitization Market			
Fraction securitized	69.8	100	100
Price of security, std	4.37	5.30	3.51
Deficit/GDP	0.93	2.73	0.00
Prob. of market collapse	11.9	0.51	0.00

Notes: All numbers are in percentage points. Moments are obtained from simulating the model for 10,000 periods. ΔC and ΔB represent the average percentage of non-durable consumption and mortgage debt, respectively, compared to the benchmark economy. Deficit/GDP corresponds exclusively to the deficit the credit guarantee policy generates.

less than proportionally to the rise in the guarantee fee. Although mortgage rates initially rise, the general equilibrium effects—such as reduced borrower indebtedness and default risk—ultimately lower mortgage spreads. The higher guarantee fee leads to lower household leverage, lower mortgage default rates, and reduced net mortgage losses for lenders. Since this policy does not generate a deficit, households do not face additional taxes. This, combined with lower deadweight losses from defaults and foreclosures, enables households to increase their consumption of nondurable goods. These effects also spill over into the securitization market, stabilizing liquidity provision and reducing the probability of market collapses.

Welfare. Borrowers and lenders are better off in the post-GFC economies than in the baseline economy. Table 12 in Appendix E shows that both post-GFC economies generate modest welfare gains for both borrowers and lenders, measured in consumption-equivalent units. Borrowers benefit primarily from lower mortgage rates and increased housing consumption. Lenders' welfare gains stem from improved allocative efficiency in the securitization market, which reduces intermediation costs and enhances risk-sharing. As a result, lenders' dividend consumption rises. Introducing a break-even guarantee fee further increases borrowers' welfare gains, while slightly reducing those of lenders. In the break-even fee scenario, borrowers experience additional welfare gains from lower mortgage defaults, reduced housing equity losses, and lower tax payments. For lenders, higher guarantee fees lead to reduced dividend payments; however, they benefit from lower deadweight losses from mortgage foreclosures and a less volatile market.

Our analysis is positive rather than normative, seeking to provide insights into the limitations and potential for improvement within the existing market design. We find that there is potential for additional welfare gains through better pricing of credit guarantees. However, the current state of the credit guarantee policy raises two further considerations that we briefly discuss next.

A primary concern with offering a complete credit guarantee is the potential moral hazard in mortgage origination. It reduces lenders' incentives to monitor loans, as they can transfer risk off their balance sheets (Gorton and Metrick (2013)). However, recent operational changes at the GSEs have mitigated this risk. Stricter conforming requirements for loan purchases—such as higher LTV and credit scores—along with enhanced scrutiny and enforcement of representations and warranties, have reduced mortgage fraud and improved loan quality. Exploring the relationship between moral hazard in loan origination and adverse selection in securitization is a promising area for further research. Theoretical work by Parlour and Plantin (2008), Vanasco (2017), and Caramp (2019) sheds light on how asset quality screening interacts with adverse selection in secondary markets. Extending our model to include originators' screening incentives could provide valuable quantitative insights.

A second major concern with the credit guarantee policy is the concentration of credit risk in a single party. As of 2022, Fannie Mae and Freddie Mac guarantee or own $5.6 trillion in residential mortgages (Federal Housing Finance Agency), exposing them to significant borrower credit risk. Since 2013, the GSEs have explored transferring some of this risk to the private sector through Credit Risk Transfers (CRT), which involve issuing Mortgage-Backed Securities (MBS) with a tranching structure to share credit losses between private investors and the GSEs during periods of high mortgage defaults. The range of CRT instruments the GSEs have tested is described by Finkelstein et al. (2018). However, CRT securities represented only 5.1% of the agencies' total market size by 2017. This raises several research questions, including the feasibility of scaling CRT, its resilience during financial crises like the GFC, and the optimal equity capital structure for the GSEs.

5 Discussion and Conclusion

Securitization plays a central role in providing liquid funds for mortgage lending. However, this source of liquidity is volatile and can rapidly expand or collapse abruptly, as observed during the credit cycle of the 2000s. Such large fluctuations are a sign of markets where information frictions play a central role. We develop a theory consistent with the U.S. mortgage market structure capable of replicating these dynamics. The model stresses the equilibrium connection between securitization and the credit market through the securitization liquidity channel (Loutskina (2011); Calem et al. (2013); Fuster and Vickery (2014)). An endogenous securitization market alleviates originators' liquidity needs and increases lending capacity. The model provides a microeconomic foundation for how securitization can enhance the allocative efficiency of assets and reduce intermediation costs in a market with heterogeneous lenders—making our framework ideal for examining other settings where asset-backed security markets play a vital role in providing liquidity to primary credit markets. However, as in practice, the benefits of securitization might be hindered by originators' private information about the quality of securitized loans. Households' income and credit risk shocks can give rise to and amplify liquidity shocks by affecting the average quality of securitized loans.

We use this framework to quantify the amplification effect of information frictions in aggregate mortgage credit and MBS issuance volumes during the GFC. We find that information frictions in the securitization market could have amplified the observed mortgage credit contraction by a multiplier ranging 1.2 to 1.3. Pointing to an important information friction multiplier of household shocks (consistent with other models that study the amplification effects of information frictions in asset markets through liquidity channels Krishnamurthy (2010), Kurlat (2013), Bigio (2015), Asriyan (2020)). The model's success in generating large fluctuations in both markets rests on two forces: (i) the severity of information frictions, which induces large fluctuations in prices in response to household shocks, and (ii) the cross-sectional characteristics of the U.S. mortgage market, which point at the importance of the securitization liquidity channel for credit provision. Our work contributes to understanding relevant factors at play in the mortgage market during the GFC by showing how household shocks that lead to surges of mortgage defaults (Mian and Sufi (2009)) together with agency problems (Downing et al. (2008); Keys et al. (2010); Adelino et al. (2019))—that maps into information and liquidity frictions—can account for dynamics at the macro level in the U.S. mortgage finance system.

On policy grounds, our theory provides insights into the rationale of credit guarantees as an instrument to stabilize liquidity in the MBS and mortgage credit markets affected by information frictions. From a positive perspective, the quantitative model shows that pricing credit guarantees in a manner that accounts for the amplification factor of information frictions may enhance the financial stability of the system—reducing the volatility of prices and quantities and the probability of a market collapse. Hence, our results complement existing studies of the credit guarantee policy of GSEs from a general equilibrium perspective.

References

Adelino, M., Gerardi, K., and Hartman-Glaser, B. (2019). Are lemons sold first? dynamic signaling in the mortgage market. *Journal of Financial Economics*, 132(1):1–25.

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Asriyan, V. (2020). Balance Sheet Channel with Information-Trading Frictions in Secondary Markets. *The Review of Economic Studies*, 88(1):44–90.

Bernanke, B. and Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *American Economic Review*, 79(1):14–31.

Bernanke, B., Gertler, M., and Gilchrist, S. (1996). The financial accelerator and the flight to quality. *The Review of Economics and Statistics*, 78:1–15.

Bigio, S. (2015). Endogenous liquidity and the business cycle. *American Economic Review*, 105(6):1883–1927.

Boissay, F., Collard, F., and Smets, F. (2016). Booms and banking crises. *Journal of Political Economy*, 124(2):489–538.

Calem, P., Covas, F., and Wu, J. (2013). The impact of the 2007 liquidity shock on bank jumbo mortgage lending. *Journal of Money, Credit and Banking*, 45(s1):59–91.

Campbell, J. Y., Giglio, S., and Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, 101(5):2108–31.

Caramp, N. (2019). Sowing the seeds of financial crises: Endogenous asset creation and adverse selection. *Manuscript*.

Chari, V. V., Kehoe, P. J., and McGrattan, E. R. (2007). Business cycle accounting. *Econometrica*, 75(3):781–836.

Chari, V. V., Shourideh, A., and Zetlin-Jones, A. (2014). Reputation and persistence of adverse selection in secondary loan markets. *American Economic Review*, 104(12):4027–70.

Chatterjee, S. and Eyigungor, B. (2015). A quantitative analysis of the u.s. housing and mortgage markets and the foreclosure crisis. *Review of Economic Dynamics*, 18(2):165–184.

Chernov, M., Dunn, B. R., and Longstaff, F. A. (2017). Macroeconomic-Driven Prepayment Risk and the Valuation of Mortgage-Backed Securities. *The Review of Financial Studies*, 31(3):1132–1183.

Chodorow-Reich, G., Guren, A. M., and McQuade, T. J. (2023). The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view. *The Review of Economic Studies*, 91(2):785–816.

Corbae, D. and D'Erasmo, P. (2020). Rising bank concentration. *Journal of Economic Dynamics and Control*, 115(C).

Demiroglu, C. and James, C. (2012). How Important is Having Skin in the Game? Originator-Sponsor Affiliation and Losses on Mortgage-backed Securities. *The Review of Financial Studies*, 25(11):3217–3258.

Downing, C., Jaffee, D., and Wallace, N. (2008). Is the Market for Mortgage-Backed Securities a Market for Lemons? *The Review of Financial Studies*, 22(7):2457–2494.

Elenev, V., Landvoigt, T., and Van Nieuwerburgh, S. (2016). Phasing out the GSEs. *Journal of Monetary Economics*, 81(C):111–132.

Elul, R. (2011). Securitization and mortgage default. Working Paper 09-21, Federal Reserve Bank of Philadelphia.

Faria-e Castro, M. (2022). Fiscal Multipliers and Financial Crises. *The Review of Economics and Statistics*, pages 1–45.

Favilukis, J., Ludvigson, S. C., and Van Nieuwerburgh, S. (2017). The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium. *Journal of Political Economy*, 125(1):140–223.

Finkelstein, D., Strzodka, A., and Vickery, J. (2018). Credit risk transfers and de facto gse reform. Working paper, Federal Reserve Bank of New York.

Frame, W. S., Fuster, A., Tracy, J., and Vickery, J. (2015). The rescue of fannie mae and freddie mac. *Journal of Economic Perspectives*, 29(2):25–52.

Fuster, A. and Vickery, J. (2014). Securitization and the Fixed-Rate Mortgage. *The Review of Financial Studies*, 28(1):176–211.

Gabaix, X., Krishnamurthy, A., and Vigneron, O. (2007). Limits of arbitrage: Theory and evidence from the mortgage-backed securities market. *The Journal of Finance*, 62(2):557–595.

Garcia-Villegas, S. (2023). The amplification effects of adverse selection in mortgage credit supply. *Journal of Housing Economics*, 62:101965.

Garriga, C., Kydland, F. E., and Šustek, R. (2017). Mortgages and monetary policy. *The Review of Financial Studies*, 30(10):3337–3375.

Garriga, C., Manuelli, R., and Peralta-Alva, A. (2019). A macroeconomic model of price swings in the housing market. *American Economic Review*, 109(6):2036–72.

Gorton, G. and Metrick, A. (2013). Chapter 1 - securitization. In Constantinides, G. M., Harris, M., and Stulz, R. M., editors, *Handbook of the Economics of Finance*, volume 2, pages 1 – 70. Elsevier.

Guerrieri, V. and Shimer, R. (2014). Dynamic adverse selection: A theory of illiquidity, fire sales, and flight to quality. *American Economic Review*, 104(7):1875–1908.

Hall, A. and Quinn, M. (2019). The mortgage prepayment decision: Are there other motivations beyond refinance and move? *Federal Reserve Bank of Philadelphia, Working Paper*.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, 95(3):739–764.

Iacoviello, M. and Neri, S. (2010). Housing market spillovers: Evidence from an estimated dsge model. *American Economic Journal: Macroeconomics*, 2(2):125–64.

Janicki, H. P. and Prescott, E. S. (2006). Changes in the size distribution of u. s. banks: 1960 - 2005. *Economic Quarterly*, 94(6).

Jiang, E., Matvos, G., Piskorski, T., and Seru, A. (2020). Banking without Deposits: Evidence from Shadow Bank Call Reports. NBER Working Papers 26903, National Bureau of Economic Research, Inc.

Jiang, W., Nelson, A. A., and Vytlacil, E. (2014). Liar's loan? effects of origination channel and information falsification on mortgage delinquency. *The Review of Economics and Statistics*, 96(1):1–18.

Jordà, O., Schularick, M., and Taylor, A. M. (2013). When credit bites back. *Journal of Money, Credit and Banking*, 45(s2):3–28.

Jordà, O., Schularick, M., and Taylor, A. M. (2016). The great mortgaging: housing finance, crises and business cycles. *Economic Policy*, 31(85):107–152.

Justiniano, A., Primiceri, G. E., and Tambalotti, A. (2015). Household leveraging and deleveraging. *Review of Economic Dynamics*, 18(1):3–20. Money, Credit, and Financial Frictions.

Justiniano, A., Primiceri, G. E., and Tambalotti, A. (2019). Credit supply and the housing boom. *Journal of Political Economy*, 127(3):1317–1350.

Kaplan, G., Mitman, K., and Violante, G. L. (2020). The housing boom and bust: Model meets evidence. *Journal of Political Economy*, 128(9):3285–3345.

Keys, B. J., Mukherjee, T., Seru, A., and Vig, V. (2010). Did securitization lead to lax screening? evidence from subprime loans*. *The Quarterly Journal of Economics*, 125(1):307.

Kiyotaki, N. and Moore, J. (2005). 2002 lawrence r. klein lecture liquidity and asset prices. *International Economic Review*, 46(2):317–349.

Krainer, J. and Laderman, E. (2014). Mortgage Loan Securitization and Relative Loan Performance. *Journal of Financial Services Research*, 45(1):39–66.

Krishnamurthy, A. (2010). Amplification mechanisms in liquidity crises. *American Economic Journal: Macroeconomics*, 2(3):1–30.

Kurlat, P. (2013). Lemons markets and the transmission of aggregate shocks. *American Economic Review*, 103(4):1463–89.

Loutskina, E. (2011). The role of securitization in bank liquidity and funding management. *Journal of Financial Economics*, 100(3):663–684.

Loutskina, E. and Strahan, P. E. (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *The Journal of Finance*, 64(2):861–889.

McCord, R. and Prescott, E. S. (2014). The financial crisis, the collapse of bank entry, and changes in the size distribution of banks. *Economic Quarterly*, 100(1):23–50.

Mian, A. and Sufi, A. (2009). The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis*. *The Quarterly Journal of Economics*, 124(4):1449–1496.

Morris, S. and Shin, H. S. (2012). Contagious adverse selection. *American Economic Journal: Macroeconomics*, 4(1):1–21.

Neil, B., Laufer, S., and Ringo, D. R. (2017). Residential mortgage lending in 2016: Evidence from the home mortgage disclosure act data,. Federal Reserve Bulletin 103, Federal Reserve Board of Governors.

Neuhann, D. (2019). Inefficient asset price booms. *SSRN Working Paper*.

Parlour, C. A. and Plantin, G. (2008). Loan sales and relationship banking. *The Journal of Finance*, 63(3):1291–1314.

Piazzesi, M. and Schneider, M. (2016). Housing and macroeconomics. In *Handbook of Macroeconomics*, volume 2, chapter Chapter 19, pages 1547–1640. Elsevier.

Piskorski, T., Seru, A., and Witkin, J. (2015a). Asset quality misrepresentation by financial intermediaries: Evidence from the rmbs market. *The Journal of Finance*, 70(6):2635–2678.

Piskorski, T., Seru, A., and Witkin, J. (2015b). Asset quality misrepresentation by financial intermediaries: Evidence from the rmbs market. *The Journal of Finance*, 70(6):2635–2678.

Shimer, R. (2014). Private Information in the Mortgage Market: Evidence and a Theory of Crises. In Bauducco, S., Christiano, L., and Raddatz, C., editors, *Macroeconomic and Financial Stability: challenges for Monetary Policy*, volume 19 of *Central Banking, Analysis, and Economic Policies Book Series*, chapter 4, pages 117–150. Central Bank of Chile.

Stanton, R., Walden, J., and Wallace, N. (2014). The industrial organization of the u.s. residential mortgage market. *Annual Review of Financial Economics*, 6(1):259–288.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3):393–410.

Vanasco, V. (2017). The downside of asset screening for market liquidity. *The Journal of Finance*, 72(5):1937–1982.

Vickery, J. and Wright, J. (2013). Tba trading and liquidity in the agency mbs market. Working paper, Federal Reserve Bank of New York.

Walentin, K. (2014). Business cycle implications of mortgage spreads. *Journal of Monetary Economics*, 67:62–77.

Appendix to Mortgage Securitization and Information Frictions in General Equilibrium

A Proofs and Derivations for the Stylized Model

A.1 Lending with Securitization and Complete Information

Lenders maximize consumption by solving the linear problem: $\max_{\{n,d,s\}} c_1 \quad \text{s.t} \quad z^j n^j q + p d^j = w + p s^j$. Given that lenders consume all their resources at the end of period 1, maximizing consumption is equivalent to maximizing the size of their lending portfolio b_1^j. Solving for n^j from the law of motion of legacy assets (2) and replacing it the budget constraint (3) obtains: $b_1^j = \{w + s^j(p - z^j q) - (p - z^j q)d^j + z^j q(1-\lambda)b^j\}\frac{1}{z^j q}$, which leads to a linear problem in trading choices:

$$\max_{\{s^j, d^j\}} \left\{ w + s^j(p - z^j q) - d^j(p - z^j q) + z^j q(1-\lambda)b^j \right\}.$$

This linear problem yields corner solutions for $\{s^j, d^j\}$, which are characterized by comparing a lender's origination cost z^j to an endogenous threshold given by the ratio of the securitization price to the discounted price of credit $\frac{p}{q}$. Let us denote such equilibrium cut-off as $z^{CI} \equiv \frac{p}{q}$. Lenders with $z^j < z^{CI}$ maximize future consumption by selling all their legacy loans and originating new ones, hence, while lenders with $z^j \geq z^{CI}$ retain their legacy, purchase securities, and originate zero new loans. In sum, lenders self-classify into two groups when trading in the securitization market: lenders-sellers and lenders-buyers. Table 5 summarizes lending and trading decisions for lenders:

Table 5: Trading and lending decisions in the complete information economy

	$z < z^{CI}$	$z \geq z^{CI}$
d	0	$\frac{w}{p}$
n	b_1	0
s	$(1-\lambda)b_0$	0

Analytical expressions for aggregates are obtained by integrating individual lenders decisions. The aggregate supply of credit is given by $N(p,q) = \int_{\underline{z}}^{\frac{p}{q}} n(z)\, \mathrm{d}F(z) = \int_{\underline{z}}^{\frac{p}{q}} \frac{w+p(1-\lambda)b_0}{zq}\, \mathrm{d}F(z)$. In the securitization market, the aggregate supply of legacy loans $S(p,q) = \int_{\underline{z}}^{\frac{p}{q}} s\, \mathrm{d}F(z) = (1-\lambda)b_0 F\left(\frac{p}{q}\right)$, and the aggregate demand of securities $D(p,q) = \int_{\frac{p}{q}}^{\bar{z}} d\, \mathrm{d}F(z) = \left(1 - F\left(\frac{p}{q}\right)\right)\frac{w}{p}$.

A.2 Lending with Securitization and Information Frictions

Given the presence of information asymmetries among lenders, lenders can now sell loans selectively; recall that s_H represents sales of loans a lender identifies as of high-quality and s_L for low-quality loans. Low-quality loans have a recovery value of zero once they fail to perform. To characterize lenders' trading decisions $\{n, d, s_H, s_L\}$, we proceed in a similar manner to the previous setup. Solving for n^j from the law of motion of legacy assets (8) and replacing it the budget constraint (6) leads to a linear problem in trading choices:

$$\max_{\{s_H^j, s_L^j, d^j\}} \left\{ w + s_H^j(p - z^j q) + p s_L^j - d^j(p - z^j q(1 - \mu(p, q))) + z^j q(1 - \lambda) b^j \right\}.$$

This linear problem yields corner solutions for $\{s_H^j, s_L^j, d^j\}$. Note that lenders may now sell loans selectively due to private information. Given any $p > 0$, all lenders have incentives to sell all their low-quality loans first, choosing $s_L^j = \lambda b_0^j$. The other two trading decisions are characterized by comparing a lender's origination cost z^j to two endogenous thresholds we denote as $\{z^S,\ z^B\} \equiv \left\{\frac{p}{q},\ \frac{p/q}{1-\mu(p,q)}\right\}$. These equilibrium thresholds split lenders into three groups: lender-seller, lender-buyer, and lender-holder. Lenders with $z \in \left[\underline{z},\ z^S\right)$: sell all their legacy loans, don't buy securities, and use all their resources to originate new loans. Lenders with $z \in \left(z^B,\ \bar{z}\right]$ retain their high-quality legacy, buy securities, and don't originate new loans. Lenders with $z \in \left[z^S,\ z^B\right]$ retain their high-quality legacy, don't buy securities, and originate new loans. Hence, lenders self-classify into lender-sellers and lender-buyers and lenders-holders, respectively. Table 6 summarizes lending and trading decisions for lenders in an economy with private information:

Table 6: Trading and lending decisions in the private information economy

	$z < z^S$	$z \in \left[z^S, z^B\right]$	$z > z^B$
d	0	0	$\frac{w+p\lambda b_0}{p}$
n	b_1	$\frac{w+p\lambda b_0}{zq}$	0
s_H	$(1-\lambda)b_0$	0	0
s_L	λb_0	λb_0	λb_0

Analytical expressions for aggregates are obtained by integrating individual lenders decisions. The aggregate supply of credit is given by:

$$\begin{aligned} N(p,q) &= \int_{\underline{z}}^{z^S} n(z)\ \mathrm{d}F(z) + \int_{z^S}^{z^B} n(z)\ \mathrm{d}F(z) \\ &= \int_{\underline{z}}^{z^S} \frac{w + pb_0}{zq}\ \mathrm{d}F(z) + \int_{z^S}^{z^B} \frac{w + p\lambda b_0}{zq}\ \mathrm{d}F(z). \end{aligned}$$

In the securitization market, the aggregate supply of legacy loans

$$\begin{aligned} S(p,q) &= \int_{\underline{z}}^{z^S} s_H^s\ \mathrm{d}F(z) + \int_{\underline{z}}^{\bar{z}} s_L\ \mathrm{d}F(z) \\ &= (1-\lambda) b_0 F\left(\frac{p}{q}\right) + \lambda b_0, \end{aligned}$$

and the aggregate demand of securities

$$D(p,q) = \int_{z^B}^{\bar{z}} d \,\mathrm{d}F(z)$$
$$= \left(1 - F\left(\frac{p/q}{1-\mu(p/q)}\right)\right)\left(\frac{w}{p} + \lambda b_0\right).$$

A.3 Proof of Proposition 1

We want to show that the discounted price of credit in an economy with access to the securitization market is strictly greater than the one in an economy without access to securitization.

Let $z^* \in (\underline{z}, \bar{z})$ and $p^* > 0$ be an equilibrium threshold and an equilibrium price resulting from clearing the credit and securitization market in a complete information economy with access to securitization. The discounted price of credit satisfies:

$$\begin{aligned}\Theta(q^{CI})^{\frac{1+\epsilon}{\epsilon}} &= (w + p^*(1-\lambda)b_0)\int_{\underline{z}}^{z^*} \frac{1}{z}\,\mathrm{d}F(z)\\ &= w\left(1 + \frac{1-F(z^*)}{F(z^*)}\right)\int_{\underline{z}}^{z^*} \frac{1}{z}\,\mathrm{d}F(z),\\ &= \frac{1}{F(z^*)} w \int_{\underline{z}}^{z^*} \frac{1}{z}\,\mathrm{d}F(z),\end{aligned}$$

where we have replaced p^* with an equivalent expression. Recall that the market clearing condition for the securitization market implies $(1-\lambda)b_0F(z^*) = (1-F(z^*))\frac{w}{p^*}$.

In the economy without access to securitization the discounted price of credit satisfies:

$$\Theta(q^{NS})^{\frac{1+\epsilon}{\epsilon}} = w\int_{\underline{z}}^{\bar{z}} \frac{1}{z}\,\mathrm{d}F(z).$$

Comparing the right-hand-side of both expressions:

$$\frac{1}{F(z^*)}\int_{\underline{z}}^{z^*} \frac{1}{z}\,\mathrm{d}F(z) > \int_{\underline{z}}^{\bar{z}} \frac{1}{z}\,\mathrm{d}F(z)$$

In other words: $\frac{\mathrm{E}[g(z)|z\leq z^*]}{\mathrm{E}[z|z\leq z^*]} \geq \mathrm{E}[g(z)]$ with $g(z) = \frac{1}{z}$.

A.4 Proof of Proposition 2

The model in section 2 presents two equilibrium outcomes: an active and an inactive securitization market. This multiplicity implies that each equilibrium outcome changes the credit supply function accordingly. Whenever the securitization market is not active, the aggregate credit supply is given by integrating lenders' lending policy functions over the domain of origination costs $N(q) = \frac{w}{q}\int_{\underline{z}}^{\bar{z}} \frac{1}{z}\,\mathrm{d}F(z)$, note that the marginal lender correspond the upper bound of the origination costs. In turn, when the securitization market is active, lenders' policy functions change to include the additional liquid funds obtained from loan sales, and the marginal lender becomes the threshold that defines the upper bound for seller-holders, z^B. The aggregate lending function is $N(p,q) = \int_{\underline{z}}^{z^S} n(z)\,\mathrm{d}F(z) + \int_{z^S}^{z^B} n(z)\,\mathrm{d}F(z) = \int_{\underline{z}}^{z^S} \frac{w+pb_0}{zq}\,\mathrm{d}F(z) + \int_{z^S}^{z^B} \frac{w+p\lambda b_0}{zq}\,\mathrm{d}F(z)$.

B Additional Derivations for the Quantitative Model

B.1 Derivation of Borrowers Default Threshold

The recursive representation of the representative borrower household problem (10) is:

$$\begin{aligned}
V(B, H; X) &= \max_{\{C,N,H',\bar{\omega}\}} u(C, H) + \beta^B \mathbb{E}_{X'|X} V(B', H'; X') \\
&s.t. \\
C + p^H(H' + \Xi(H')) + m(1-\lambda(\bar{\omega}))B &= (1-\lambda(\bar{\omega}))\mu_\omega(\bar{\omega})p^H H + qN + Y + T^B \\
B' &= (1-\phi)(1-\lambda(\bar{\omega}))B + N \\
B' &\leq \pi p^H H' \\
& N \geq 0, \;\; H' \geq 0.
\end{aligned}$$

where $\{p^H, q\}$ are the price of housing and the discounted price of credit. Recall that the total mortgage payment $m = \kappa(1-\phi) + \phi$, and $\phi = \delta(1-\eta) + \eta$ is the effective maturity of aggregate debt after taking into account prepayments η.

Recall that household's members are subject to an idiosyncratic housing valuation shock $\omega_t^i \sim G_\omega$ with constant mean μ_ω and time-varying volatility $\sigma_{\omega_t} = Var[\omega_t^i]^{\frac{1}{2}}$. Housing valuation shocks proportionally lower the value of a member's housing holdings to $\omega_t^i p_t^H h_t$. Members optimally decide to default on or repay according to the default function $\iota(\omega^i) : [0, \infty) \to \{0, 1\}$. When a member defaults on b_t, $\iota(\omega^i) = 1$, she also loses her stock of housing good h_t through foreclosure. The aggregate household default rate is defined as:

$$\begin{aligned}
\lambda(\bar{\omega}) &= \int_0^\infty \iota(\omega) g_\omega(\omega) d\omega \\
&= Pr[\omega^i \leq \bar{\omega}] \\
&= \int_0^{\bar{\omega}} g_\omega d\omega \\
&= G_\omega(\bar{\omega}; \chi_1, \chi_2)
\end{aligned}$$

where G_ω denotes the CDF of housing individual shocks. We assume G_ω is a Gamma distribution characterized by parameters $\{\chi_1, \chi_2\}$. The tail conditional expectation of housing shocks is given by:

$$\begin{aligned}
\mu_\omega(\bar{\omega}) &= \mathbb{E}[\omega_i | \omega_i \geq \bar{\omega}; \chi] \\
&= \mu_\omega \frac{1 - G_\omega(\bar{\omega}; 1+\chi_1, \chi_2)}{1 - G_\omega(\bar{\omega}; \chi_1, \chi_2)}
\end{aligned}$$

also, notice that

$$(1 - \lambda(\bar{\omega}))\mu_\omega(\bar{\omega}) = \mu_\omega[1 - G_\omega(\bar{\omega}; 1+\chi_1, \chi_2)].$$

The optimal default threshold $\bar{\omega}$ can be derived by taking First Order Conditions of the above problem w.r.t $\{N, H', \bar{\omega}\}$:

$$
\begin{aligned}
N \quad &: \qquad U_c(q - \tilde{\xi}) = -\beta^B \mathbb{E}[V'_B] \\
H' \quad &: \qquad U_c p^H (1 + \Xi_{H'} - \pi\tilde{\xi}) = \beta^B \mathbb{E}[V'_H]
\end{aligned}
$$

where $V'_B = \partial V / \partial B'$ and $V'_H = \partial V / \partial H'$, and ξ is the Lagrange multiplier associated to the borrowing constraint, and $\tilde{\xi} = \xi / U_c$.

By the Envelope Theorem:

$$
\begin{aligned}
V_B &= -U_c(1 - \lambda(\bar{\omega}))(q(1 - \phi) + m) \\
V_H &= U_c(1 - \lambda(\bar{\omega}))\mu_\omega(\bar{\omega}) p^H + U_H
\end{aligned}
$$

Combining equations from the Envelope theorem and the F.O.C. yields

$$
q = \tilde{\xi} + \beta^B \mathbb{E}\left[\frac{U'_c}{U_c}(1 - \lambda(\bar{\omega}'))(q'(1 - \phi') + m')\right] \tag{26}
$$

$$
p^H (1 + \Xi_{H'} - \pi\tilde{\xi}) = \beta^B \mathbb{E}\left[\frac{U'_c}{U_c}\left((1 - \lambda(\bar{\omega}'))\mu_\omega(\bar{\omega}') p^{H'} + \frac{U'_H}{U'_C}\right)\right] \tag{27}
$$

The derivatives of $\lambda(\bar{\omega})$ and $\mu_\omega(\bar{\omega})$ functions w.r.t. $\bar{\omega}$ are

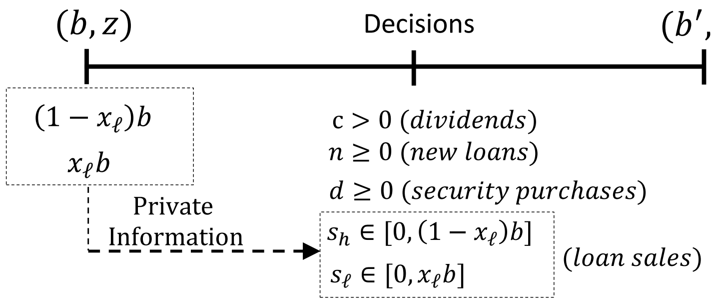
$$
\begin{aligned}
\frac{\partial \lambda(\bar{\omega})}{\partial \bar{\omega}} &= \frac{\partial}{\partial \bar{\omega}} \int_0^{\bar{\omega}} g_\omega(\omega) d\omega \\
&= g_\omega(\bar{\omega}) \\
\frac{\partial [(1 - \lambda(\bar{\omega}))\mu_\omega(\bar{\omega})]}{\partial \bar{\omega}} &= \frac{\partial}{\partial \bar{\omega}} \int_{\bar{\omega}}^{\infty} \omega g_\omega(\omega) d\omega \\
&= -\bar{\omega} g_\omega(\bar{\omega})
\end{aligned}
$$

Taking the F.O.C. of the value function w.r.t. $\bar{\omega}$ yields:

$$
\begin{aligned}
U_c(-\bar{\omega} g_\omega(\bar{\omega}) p^H H + g_\omega(\bar{\omega}) m B) + \tilde{\xi}(1 - \phi) g_\omega(\bar{\omega}) B &= -\beta^B \mathbb{E}\left[\frac{\partial V}{\partial B'} \frac{\partial B'}{\partial \bar{\omega}}\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega} p^H H + m B) + U_c \tilde{\xi}(1 - \phi) g_\omega(\bar{\omega}) B &= \beta^B \mathbb{E}\left[\frac{\partial V}{\partial B'}(1 - \phi) g_\omega(\bar{\omega}) B\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega} p^H H + m B + \tilde{\xi}(1 - \phi) B) &= (1 - \phi) g_\omega(\bar{\omega}) B \left[\beta^B \mathbb{E}[V_{B'}]\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega} p^H H + m B + \tilde{\xi}(1 - \phi) B) &= -(1 - \phi) g_\omega(\bar{\omega}_h) B U_c (q - \tilde{\xi}) \\
\bar{\omega} &= \frac{B}{p^H H}[m + (1 - \phi) q]
\end{aligned} \tag{28}
$$

B.2 Timeline for lenders decisions

Figure 8: Timeline for lenders decisions



Source: Author's elaboration. Notation: b represents the lender's portfolio of loans and z is the lender's draw of origination cost at the beginning of the period. The fraction of low-quality loans is denoted by x_ℓ.

B.3 Additional Derivations for Lenders

Here, we characterize lenders' policy functions and derive closed-form expressions for aggregate quantities in the securitization market. We drop j subscripts and time indexing for ease of notation. Following Kurlat (2013), the lender's problem exhibits similar properties: (i) the lender holds a single asset, making the budget set linear in b, and (ii) lenders have homothetic preferences, resulting in policy functions that are linear in b. These features, combined with i.i.d. idiosyncratic origination costs across lenders and over time, significantly simplify the problem. Specifically, for given p, q, μ, the aggregates S_h, S_ℓ, D and the market-clearing values p, q, μ are independent of the distribution of b. Thus, the joint distribution $\Gamma(b, z)$ is not required to compute aggregate quantities and prices; B serves as a sufficient statistic.

Trading and lending decisions. To characterize trading decisions, we treat portfolio lending decisions b' as given. The lender's problem in (17) reduces to maximizing dividends c by choosing $\{n, s_h, s_\ell, d\}$. This involves solving a linear problem derived by combining the budget constraint (18) with the portfolio law of motion (16), as shown below.

$$
\begin{aligned}
V(b, z, X) = &\max_{\{c, n, b', d, s_h, s_\ell\}} \left[u(c) + \beta^L \mathbb{E}_{X'|X} V(b', z', X') | X \right] \\
&s.t. \\
c + zqb' + \gamma b' = &(zq + \gamma)(1 - x_\ell + x_\ell(1 - \rho))(1 - \phi)b + ((1 - x_\ell)m_h + x_\ell m_\ell)b - T^L b \\
&+ s_h \left(p - m_h - (zq + \gamma)(1 - \phi)\right) \\
&+ s_\ell \left(p - m_\ell - (zq + \gamma)(1 - \phi)(1 - \rho)\right) \\
&+ d \left((zq + \gamma)(1 - \phi)(1 - \mu) + m_d - p(1 - \tau)\right)
\end{aligned}
$$

Each lender takes prices p, q, μ as given and derives trading decisions by comparing static payoffs. For low-quality loan sales (s_ℓ), a lender with draw z has no incentive to retain a low-quality loan if $p > m_\ell + \Theta$, where $\Theta \equiv (\bar{z}q + \gamma)(1-\phi)(1-\rho)$. In this case, the lender sells all low-quality loans, setting $s_\ell = x_\ell b$ at the corner solution in (20). For high-quality loan sales (s_h), the decision depends on whether the internal valuation of the loans, $m_h + (zq+\gamma)(1-\phi)$, exceeds the market price. Taking into account the portfolio constraint in (19) yields:

$$s_h = \begin{cases} (1-x_\ell)b & \text{if} \quad z < z^S \\ 0 & \text{if} \quad z \geq z^S \end{cases}$$

where $z^S \equiv \frac{1}{q}\frac{p-m_h}{(1-\phi)} - \frac{\gamma}{q}$. Likewise, the condition for the decision to purchase securities d is:

$$d = \begin{cases} > 0 & \text{if} \quad z > z^B \\ 0 & \text{otw} \end{cases}$$

where $z^B \equiv \frac{1}{q}\frac{p-m_h}{(1-\phi)} - \frac{\gamma}{q}$, $z^B \equiv \frac{1}{q}\frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)} - \frac{\gamma}{q}$. For a lender, n and d are alternative forms of lending resources. When the net cost of doing it through security purchases is lower, the optimal decision is to set new loans to zero.

Given a lender's draw of origination cost $z \in [\underline{z}, \bar{z}]$, her trading decisions are characterized according to cutoffs $\{z^S, z^B\}$.[35] Lenders self-classify in three types:

- Seller. A lender with $z \in \left[\underline{z},\ z^S\right)$ and $\{d = 0,\ s_h = (1-x_\ell)b,\ s_\ell = x_\ell b\}$. Replacing these policy functions in (16) obtains the origination policy function: $n = b'$.
- Buyer. A lender with $z \in \left(z^B,\ \bar{z}\right]$ and $\{d > 0,\ s_h = 0,\ s_\ell = x_\ell b\}$. Replacing these policy functions in (16) obtains policy functions for $d = \frac{b'-(1-x_\ell)(1-\phi)b}{(1-\mu)(1-\phi)}$ and $n = 0$.
- Holder. A lender with $z \in \left[z^S,\ z^B\right]$ and $\{d = 0,\ s_h = 0,\ s_\ell = x_\ell b\}$. Replacing these decisions in (16) obtains $n = b' - (1-x_\ell)(1-\phi)b$, with $n \geq 0$.

If no positive price clears supply and demand, the securitization market becomes inactive, and the loan quality distinction within a lender's portfolio is irrelevant. In this case, all lenders make trivial trading decisions: $\{d = 0, s_h = 0, s_\ell = 0\}$. Substituting these choices into (16) yields the origination decision: $n = b' - (1-\lambda(\bar{\omega}))(1-\phi)b \geq 0$, given $\rho x_\ell = \lambda(\bar{\omega})$ for all lenders.

[35] These equilibrium cut-offs are well defined in the support $[\underline{z}, \bar{z}]$. Also, the fraction of securitized low-quality loans satisfies $\mu_t < 1$ as $S_{\ell_t} < S_t$, and the foreclosure recovery function satisfies $\Psi_t < 1$ for the relevant set of underlying parameters.

Aggregates in the Securitization Market. Using these expressions, we can derive closed-form solutions for aggregate quantities in the securitization market and aggregate credit supply. Since $z \sim i.i.d.$ and policy functions are linear in b, the aggregate supply and demand for securities S, D are independent of the joint distribution $\Gamma(b, z) = F(z)G(b)$, where $F(z)$ and $G(b)$ are the respective CDFs. From the definitions, the expressions for supply and demand in the securitization market are given by:

1. Aggregate Supply of loans, S

$$\begin{aligned} S &= S_\ell + S_G \\ &= \int_{\underline{z}}^{\bar{z}} s_\ell(b, z, X) d\Gamma(b, z) + \int_{\underline{z}}^{z^S} s_h(b, z, X) d\Gamma(b, z) \\ &= B \left[\frac{\lambda(\bar{\omega}_t)}{\rho} + (1 - \frac{\lambda(\bar{\omega}_t)}{\rho})(1 - \phi) F(z^S) \right] \end{aligned}$$

2. Aggregate Demand of securities, D

$$\begin{aligned} D(X) &= \int_{z^B}^{\bar{z}} d(b, z, X) d\Gamma(b, z) \\ &= \int_{z^B}^{\bar{z}} \frac{b' - (1 - \lambda)(1 - \phi) b}{(1 - \mu)(1 - \phi)} \, d\Gamma(b, z) \\ &= \frac{1 - F(z^B)}{1 - \mu} B \left[\frac{\beta(1 - \mu)}{p(1 - \tau) - m_d} \left((1 - \frac{\lambda}{\rho}) m_h + \frac{\lambda}{\rho} p - T^L \right) - (1 - \beta)(1 - \frac{\lambda}{\rho}) \right] \end{aligned}$$

where the equilibrium cutoffs are $\{z^S, z^B\} \equiv \left\{ \frac{1}{q} \frac{p - m_h}{(1 - \phi)} - \frac{\gamma}{q}, \frac{1}{q} \frac{p(1 - \tau) - m_d}{(1 - \mu)(1 - \phi)} - \frac{\gamma}{q} \right\}$.

The price of debt q does not depend on the distribution of debt holdings across lenders because the market clearing condition in the credit market is a function only of the aggregate level of debt B.

1. Demand of credit from borrowers depends only on aggregates states $\{B, H, \lambda(\bar{\omega}), Y\}$ through the policy function of $B'(B, H; X)$. Hence, the distribution of debt claims is irrelevant from the stand point of the borrower:

$$N = B'^B - (1 - \lambda(\bar{\omega}))(1 - \phi) B^B$$

2. Supply of credit from lenders correspond to the integral across the individual originations n. Given that lending policy functions are linear in b, the aggregate supply of lending is linear in the aggregate amount of debt claims in the economy B. This can be seen from the aggregation of the origination decisions: $\int n(b, z; X) d\Gamma(b, z)$.

   Similar to the stylized model, there are two possible expressions for the aggregate supply of credit. The first case when the securitization market is active,

$$
\begin{aligned}
N^{\text{seller}} &= \int_{\underline{z}}^{z^S} n(b,z,X)d\Gamma(b,z) \\
&= \beta\left[p - T^L\right]\int_{\underline{z}}^{z^S} \frac{1}{zq+\gamma} b\ dFz \\
N^{\text{holder}} &= \int_{z^S}^{z^B} n(b,z,X)d\Gamma(b,z) \\
&= \int_{z^S}^{z^B} \left[b'(b,z,X) - (1-x_\ell)(1-\phi)b\right] d\Gamma(b,z) \\
&= \beta\left[(1-\frac{\lambda}{\rho})m_h + \frac{\lambda}{\rho}p - T^L\right] B \int_{z^S}^{z^B} \frac{1}{zq+\gamma} dFz \\
&\quad -(1-\beta)(1-\frac{\lambda}{\rho})(1-\phi)B\left(F(z^B) - F(z^S)\right) dFz \\
\int n(b,z;X)d\Gamma(b,z) &= N^{\text{seller}} + N^{\text{holder}}
\end{aligned}
$$

The case when there is no trade in securitization markets and each lender originates loans using its own technology.

$$
\begin{aligned}
\int_{\underline{z}}^{\overline{z}} n(b,z;X)d\Gamma(b,z) &= \int_{\underline{z}}^{\overline{z}} b' - (1-\lambda)(1-\phi)bd\Gamma(b,z) \\
&= \frac{\beta}{q}\left[(1-\lambda(\bar{\omega}))m + \lambda(\bar{\omega})\Psi\right] B \int_{\underline{z}}^{\overline{z}} \frac{1}{z} dFz - (1-\beta)(1-\phi)(1-\lambda)B
\end{aligned}
$$

Budget sets by lender type: Replacing the optimal origination and trading decisions in the budget constraint and in the law of motion of lenders, problem (17), obtains:

- Buyers:

$$
c + \frac{p(1-\tau) - m_d}{(1-\mu)(1-\phi)} b' = \left[(1-x_\ell)\left(\frac{p(1-\tau)-m_d}{(1-\mu)} + m_h\right) + x_\ell p - T^L\right] b
$$

- Sellers:

$$
c + (zq+\gamma)b' = \left[p - T^L\right] b
$$

- Holder:

$$
c + (zq+\gamma)b' = \left[(1-x_\ell)\left((zq+\gamma)(1-\phi) + m_h\right) + x_\ell p - T^L\right] b
$$

C Computational Algorithm

C.1 Solving the General Equilibrium Model

The model features strong nonlinearities arising from the interactions of lenders in the securitization market. In order to capture such nonlinearities we solve the model by global solution methods in a discrete state space for endogenous and exogenous state variables. Exogenous states are characterize by a joint state space $(\sigma_\omega, Y) \in \mathcal{L} \times \mathcal{Y}$, and an associated transition Π_s matrix. The aggregate endogenous states for debt and housing holdings are given by the space $\mathcal{B} \times \mathcal{H}$. The space of all aggregate state is given by $\mathcal{X} \equiv \mathcal{L} \times \mathcal{Y} \times \mathcal{B} \times \mathcal{H}$. Because the problem is computationally demanding, we set a grid of 40 points for $\mathcal{B}$, 40 points for $\mathcal{H}$, and 21 points for the joint state space (σ_ω, Y). Solving the model consists on finding:

- policy, and value functions for borrower's problem;
- schedule of prices $\{q(X), p(X)\}$ for all realizations of the aggregate state vector $X \in \mathcal{X}$.

We perform value function iteration to solve for borrowers' policy functions, and use the closed form characterization of lender's decision rules to solve for the system of market clearing conditions within the space of aggregate states.

$$
\begin{aligned}
N(q; X) &= N^S(p, q; X) \\
D(X) &= S(X)
\end{aligned}
$$

C.2 Welfare evaluation

This section explain the approach we follow for the welfare evaluation. We compute two metrics, one based in the consumption equivalent units of the non-durable consumption good, and another taking into account changes in the services from the housing good.

Define $\tilde{V}(\tilde{c}, \tilde{h})$ as the lifetime utility under the benchmark economy and $V(c, h)$ the utility under an alternative economy subject to the same aggregate exogenous states S_t. We evaluate welfare as the fraction of non-durable consumption allocation, in the benchmark economy, a household will be willing to forego in order to be indifferent to live under the alternative specification. Hence, the permanent consumption loss $\tilde{\alpha}$ is such that:

$$
\begin{aligned}
\mathbb{E}_{t|t_0} V(c_t, h_t; S_t) &= \mathbb{E}_{t|t_0} V((1-\tilde{\alpha})\tilde{c}_t, \tilde{h}_t; S_t) \\
&= \sum_{t=0}^{\infty} \beta^t \left((1-\theta) \log((1-\tilde{\alpha})\tilde{c}_t) + \theta \log \tilde{h}_t \right) \\
&= \frac{(1-\theta)\log(1-\tilde{\alpha})}{1-\beta} + \sum_{t=0}^{\infty} \beta^t ((1-\theta) \log \tilde{c}_t + \theta \log \tilde{h}_t) \\
\log(1-\tilde{\alpha}) &= \frac{1-\beta}{1-\theta} \left[\mathbb{E}_{t|t_0} V(c_t, h_t; S_t) - \mathbb{E}_{t|t_0} V(\tilde{c}_t, \tilde{h}_t; S_t \right] \\
\tilde{\alpha} &= 1 - \exp\left[\frac{1-\beta}{1-\theta} \mathbb{E}_{t|t_0} (V - \tilde{V}) \right]
\end{aligned}
$$

$\tilde{\alpha} > 0$ indicates welfare losses associated to transitionning from the benchmark economy to the alternative economy, as the households is willing to sacrifice a positive amount of her benchmark consumption allocation in order to be indifferent with the alternative economy.

D Calibration Appendix

D.1 Time Series and Cross-sectional Statistics

Table 7: Mortgage Credit and Securitization Volumes in the U.S.

Mortgage market	Pre-GFC 90-06	Post-GFC 13-18	All 90-18
Loans sold/securitized (%)	63.5	71.4	67.3
Securitization by large originators (%)	64.5	77.9	70.0
Securitization by mortgage companies (%)	83.7	94.8	87.3
Correlation (sales, lending)	0.96	0.98	0.97
GSEs market share of RMBS issuance	0.69	0.95	0.81

Source: Loan Application Registries(LAR) and Reporter Panel from the Home Mortgage Disclosure Act (HMDA) dataset, years 1990 to 2018. Loans sold or securitized are measured as the average dollar amount of loans sold or securitized divided by the total dollar amount originated in a year by a reporting institution. Large originators are those originating more than the annual cross-sectional average. The reported correlation reflects the average relationship between the volume of loans originated and the volume sold or securitized across institutions. Data on RMBS issuance market share, available from 1996 onward, is sourced from SIFMA.

Table 8 summarizes average moments of the cross-sectional distribution of originators by loan volume.[36] On average, the top 1% of originators accounted for 64% and the top 10% for 90% of total mortgage lending.[37] A comparable concentration is observed in funding sources, where Stanton et al. (2014) report that the top 40 lenders accounted for 96% of residential originations in 2006. Our model calibration matches these moments, as shown in Section 4.1, where they play a key role in shaping equilibrium outcomes and the amplification effect of information frictions (Section 4).

[36] Results are similar when restricting to home purchase, conventional, one-to-four family, owner-occupied loans.

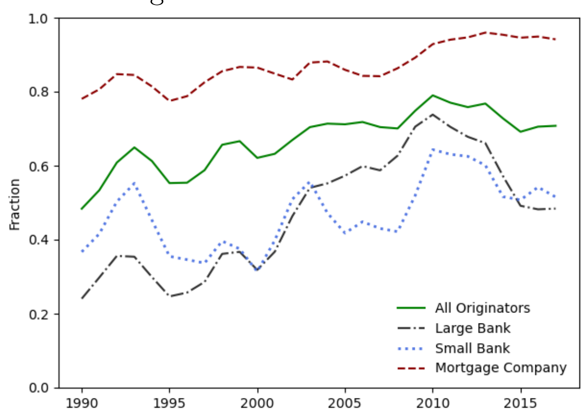
[37] This pattern holds across different types of institutions (e.g., banks, thrifts, mortgage companies) and aligns with findings by Corbae and D'Erasmo (2020), McCord and Prescott (2014), and Janicki and Prescott (2006) on trends in the banking industry.

Table 8: Moments of the distribution of mortgage lending

Moments	90-18
Market share top 1%	0.64
Market share top 10%	0.90
Market share top 25%	0.96
Lending top 10% to bottom 90%	9.30
Mean/median	18.6

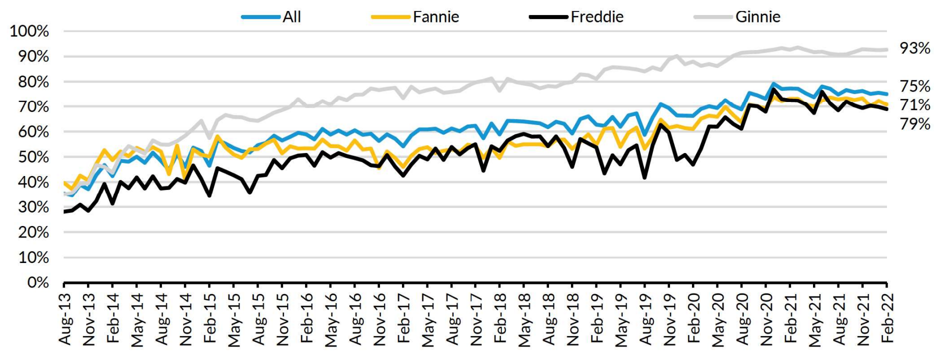
Source: Loan Application Registries(LAR) and Reporter Panel from the Home Mortgage Disclosure Act (HMDA) dataset, years 1990 to 2018. Average cross-sectional moments for new residential mortgage credit originated in a given year by each reporter in HMDA.

Figure 9: Fraction securitized



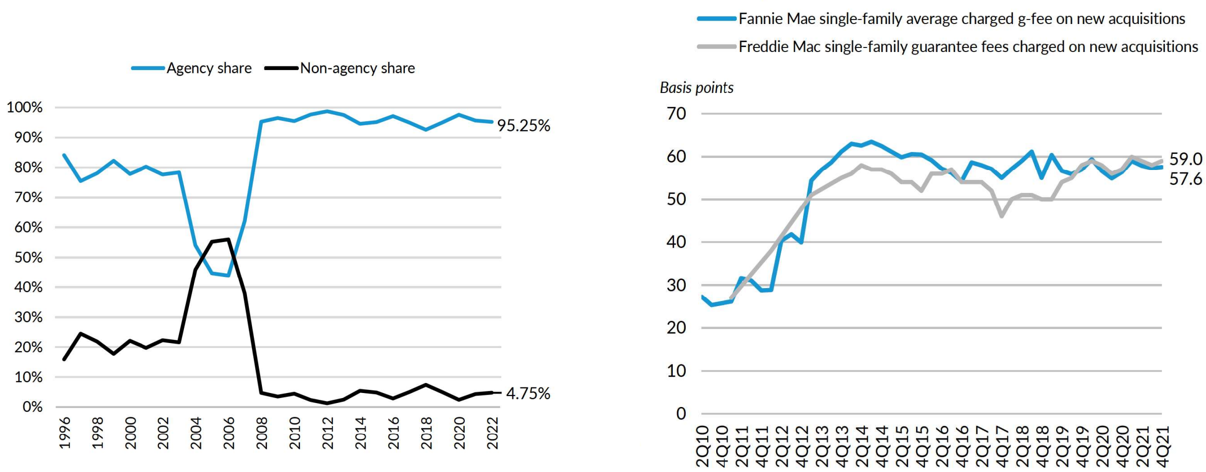
Authors elaboration. Source: HMDA LARs and Reporter Panel, 1990–2018. The fraction of sold or securitized mortgages is the cross-sectional average of the total dollar amount of mortgages sold or securitized, divided by the total dollar amount of mortgage lending for the reporter institution, based on loans originated in the reported year. Large banks are those with assets of $1 billion or more, while small banks have assets under $1 billion.

Figure 10: Non-bank origination share of agency residential mortgage lending.



Source: Urban Institute. Reproduced from the Urban Institute Housing Finance Chartbook, March 2022. Non-bank institutions include affiliated and independent mortgage companies.

Figure 11: GSEs in the Residential MBS Market

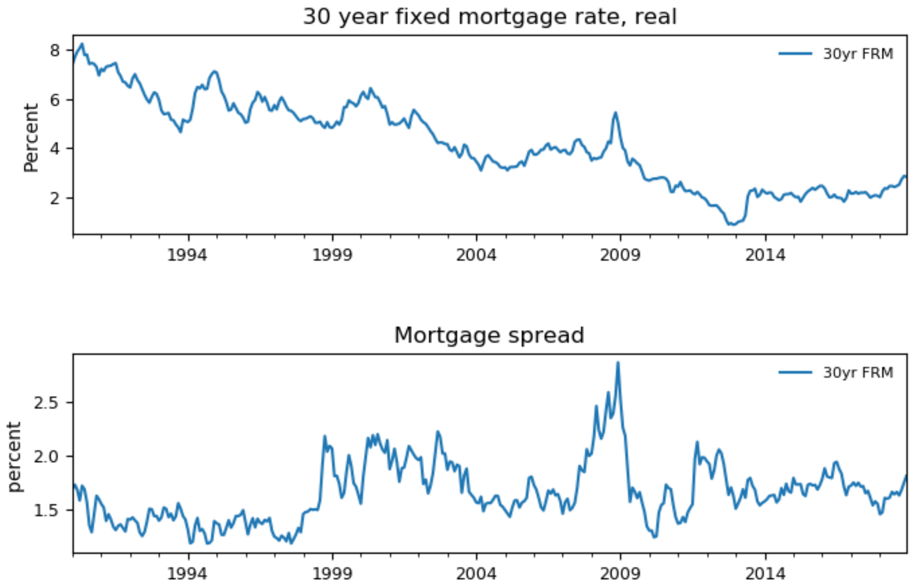


(a) Shares of residential MBS issuance

(b) Effective Guarantee fees

Reproduced from the Urban Institute Housing Finance Chartbook, March 2022. Panel (a). Agency corresponds to MBS issuance by the Government Sponsored Enterprises Freddie Mac and Fannie Mae. Non-agency corresponds to private securitizers. Panel (b) shows the average guarantee fees charge by Freddie Mac and Fannie Mae on mortgage purchases from mortgage originators.

Figure 12: Historic mortgage interest rates



Source: Freddie Mac Primary Mortgage Market Survey 2018. Mortgage spread is the different between the 30 year fixed mortgage rates and a 10 year treasury bill rate. Mortgage rate correspond to the real rate obtained from subtracting 10 year expected inflation to the nominal 30 year fixed mortgage rate.

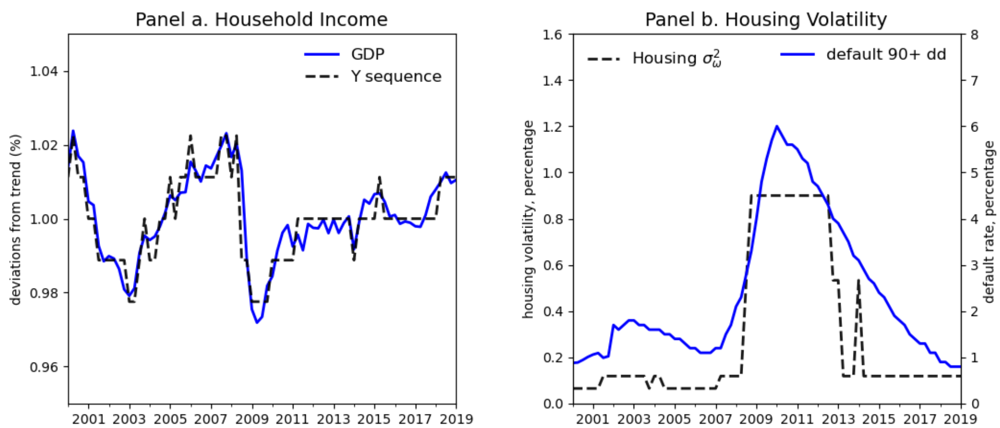
Table 9: Historic average mortgage rates

Description	90-06	13-18	90-18
Mortgage rate, mean	5.20	2.22	4.10
Mortgage rate, std	1.46	0.38	1.56
Mortgage spread, mean	1.60	1.68	1.66
Mortgage spread, std	0.28	0.10	0.29

Source: Freddie Mac Primary Mortgage Market Survey 2018. Mortgage spread is the difference between the 30 year fixed mortgage rate and a 10 year treasury bill rate. Mortgage rate correspond to the real rate obtained from subtracting the 10 year expected inflation to the nominal 30 year fixed mortgage rate.

D.2 Households Income and Default Rates

Figure 13: Income and default processes



Panel a. The solid blue line represents the cyclical component of GDP, while the black dashed line shows the estimated discretized income sequence used in the model. Panel b. The dashed black line represents the sequence of housing valuation shocks, while the solid blue line shows the default rate, calculated as the percentage of delinquent single-family residential mortgage loans (90 days or more past due, or in foreclosure) reported by National Mortgage Database (NMDB).

D.3 Estimation of Exogenous Processes

Household's income and housing valuation shocks. We model the variance of the housing valuation shocks and borrower households' income Y as a first-order joint Markov process. For income, we use the Hodrick-Prescott (HP) cyclical component of GDP to estimate the state space and transition matrix. First, we estimate an auto-regressive model of first order, AR(1), for a long-time series from 1960 to 2019. We discretize this processes by the Rouwenhorst method into a Markov chain with seven states:

y_1	y_2	y_3	y_4	y_5	y_6	y_7
0.966	0.978	0.989	1.000	1.011	1.022	1.034

with the corresponding transition probability matrix Π_Y,

	y_1	y_2	y_3	y_4	y_5	y_6	y_7
y_1	0.635	0.300	0.059	0.006	0.000	0.000	0.000
y_2	0.050	0.654	0.253	0.040	0.003	0.000	0.000
y_3	0.004	0.101	0.666	0.204	0.024	0.001	0.000
y_4	0.000	0.012	0.153	0.670	0.153	0.012	0.000
y_5	0.000	0.001	0.024	0.204	0.666	0.101	0.004
y_6	0.000	0.000	0.003	0.040	0.253	0.654	0.050
y_7	0.000	0.000	0.000	0.006	0.059	0.300	0.635

Similar to Elenev et al. (2016), we assume that housing valuation shocks, ω_t, follow a Gamma distribution with cdf $\Gamma(\omega; \chi_{t,0}, \chi_{t,1})$ characterized by shape and scale parameters $\{\chi_{t,0}, \chi_{t,1}\}$. The mean is kept constant at $\mu_\omega = 0.971$, to match an annual depreciation of 2.91% for private residential capital (BEA). We also let the cross-sectional variance $\sigma^2_{t,\omega}$ follow a three-state Markov process with high and low regimes. Elenev et al. (2016) introduces this structure on $\sigma^2_{t,\omega}$ to capture exogenous forces affecting mortgage credit risk that fit high-volatility episodes like the foreclosure crises experienced in 2007-12. However, we depart from their work in that we use available FHFA data on house price indexes (for all 51 states from 1975 to 2020) to estimate the Markov processes for the cross-sectional variance. First, we split the sample into low-volatility periods (1991-2004, 2010-2020) and high-volatility periods (1975-1990, 2005-2009) based on the years with cross-sectional variance below—and above— the unconditional mean in our sample. The estimated state space of σ^2_ω for the low-volatility period is

$\sigma^2_{\omega_{L,1}}$	$\sigma^2_{\omega_{L,2}}$	$\sigma^2_{\omega_{L,3}}$
0.00025	0.00155	0.00253

with transition probability matrix

$$\begin{bmatrix} 0.29 & 0.50 & 0.21 \\ 0.25 & 0.50 & 0.25 \\ 0.21 & 0.50 & 0.29 \end{bmatrix}$$

For the high-volatility regime, the estimated state space falls short in generating default rates as high as those observed during the 2007-2012 foreclosure crisis. A possible limitation of the FHFA house price indexes data—which rely on sales prices and appraisal values for mortgages acquired or guaranteed by Fannie Mae and Freddie Mac—is that properties located in metropolitan areas with a higher proportion of non-conforming loans may be inadequately represented as GSEs predominantly deal with conforming loans. This observation is relevant for our estimation because these metropolitan areas are recognized for their significant fluctuations in house prices. To overcome this, we calibrate the two highest states $\{\sigma^2_{\omega_{H,2}}, \sigma^2_{\omega_{H,3}}\}$ to target a default rate of 4.05% in crisis times and unconditional default rates of 2.01% in line with the national 90 days or more delinquency rate from NMDB. The estimated transition matrix remains unchanged. The state space of σ^2_ω for the high-volatility period is

$\sigma^2_{\omega_{H,1}}$	$\sigma^2_{\omega_{H,2}}$	$\sigma^2_{\omega_{H,3}}$
0.0025	0.0059	0.0093

with transition probability matrix

$$\begin{bmatrix} 0.40 & 0.47 & 0.14 \\ 0.23 & 0.53 & 0.23 \\ 0.14 & 0.47 & 0.40 \end{bmatrix}$$

We then combine the high-volatility state space for the housing valuation shocks with the three lowest states of the income process and the low-volatility state space with the top four income states. Thus, the joint distribution for income and housing shocks features 21 states. Table 10 presents moments from the joint Markov process for a simulation of 100,000 periods. The Markov process fits well the unconditional means and standard deviations for income, and yields a negative correlation between income and the volatility of housing valuation shocks.

Table 10: Fitted moments for income and housing volatility processes

	Income, Y	Volatility, σ_ω^2
mean	1.0000	0.0030
std	0.0137	0.0026
persistence (ρ)	0.8529	0.5542
$\mathbb{E}[X\|\text{crisis}]$	0.9847	0.0059
$\mathbb{E}[X\|\text{normal}]$	1.0080	0.0015
corr(Y, σ_ω^2)	-0.6433	

Prepayment risk. Mortgage prepayments occur for various reasons: moving to a different house, saving in interest payments (reducing the debt burden), refinancing debt to benefit from lower interest rates, or refinancing to take on more debt (cash-out). We abstract from modeling the household prepayment decisions and introduce prepayment risk as an exogenous process positively correlated with the household's income.[38] Our specification, although reduced form, captures a household's prepayment risk arising from paying off mortgages to save in interest payments and from housing moving motives. Motivated by Gabaix et al. (2007), who conceptualized prepayment uncertainty as an error surrounding the average prepayment forecast, we let households' prepayment rates follow an analogous exogenous process:

$$\eta_t = \bar{\eta} + \epsilon_\eta,$$

where $\bar{\eta}_t$ denotes the average prepayment rate and ϵ_η represents disturbances that correlate with household income. Based on SIFMA reports—"Long Term for conventional 30-yr mortgages with a coupon of 5% from Fannie Mae and Freddie Mac and Ginnie Mae—we set $\bar{\eta} = 0.12$ and let $\epsilon_\eta \in [-0.03, 0.0, 0.03]$ be a three-state Markov process such that $\epsilon_\eta < 0$ conditional on being in the bottom two states of aggregate income, $\epsilon_\eta > 0$ conditional on being in the top two states of

[38] Gabaix et al. (2007) document that, controlling for interest rates, households are more likely to prepay mortgages in good macroeconomic states than in bad ones, and that mortgage prepayments correlate positively with aggregate consumption and house price growth. Although changes in interest rate are a main driver of refinancing motives, Hall and Quinn (2019) finds that an important fraction of prepayments arises due to motives different from interest rate changes, like to paying off debt and moving decisions.

aggregate income, and $\epsilon_\eta = 0$ for other income states. The calibrated prepayment process replicates a mean prepayment rate of 12% with std 2.5%, a positive correlation with aggregate consumption growth, a positive correlation with housing expenditures, and a negative correlation with mortgages spread consistent with the findings in Gabaix et al. (2007).

Government Policy. In practice, GSEs charge a guarantee fee to mortgage originators quoted in basis points over the interest rate contracted with the borrowers, i.e. $r_t^* = r_t + g_f$, where r_t is the contracted interest rate and g_f is the GSEs' guarantee fee. We use the standard formula of the discounted price of a long-term mortgage bond based on future cash flows m_t: $q_t = \sum_{t=1}^{\infty} \frac{m_t}{1+r_t}$ without and with guarantee fee $q_t + \gamma_t = \sum_{t=1}^{\infty} \frac{m_t}{1+r_t^*}$, to link the policy g_f to the variable γ_t representing the guarantee fee in the model. The guarantee fee, in terms of discounted price units, is the value of γ_t that replicates the spread $r_t^* - r_t = g_f$. Straightforward algebra obtains $\gamma_t = \left(\frac{1}{q_t} - \frac{g_f}{m_t}\right)^{-1} - q_t$, which is the fee paid by originators in the model in equation (18).

D.4 Data Sources

Home Mortgage Disclosure Act - HMDA

This section details the data set and variable construction used in the model's calibration, Section 4.1. HMDA requires mortgage originators—banks and non-bank institutions—to collect and publicly disclose information about their mortgage lending activity, including loan characteristics. HMDA is considered nearly comprehensive for U.S. home lending (Neil et al., 2017).

I construct a panel of mortgage originators for 1990–2018. Using Loan Application Registries (LAR), I compute annual aggregate volumes, both in dollars and loan counts, for mortgages originated and sold in the securitization market by each institution. Consistent with standard practice, I restrict the sample to conventional, one-to-four family, owner-occupied dwellings, including home purchase and refinance loans. I also utilize the HMDA Reporter Panel, which provides details on originators, such as institution type (Bank Holding Company, Independent Mortgage Company, or Affiliate Mortgage Company), supervisory agency, and assets. Merging the LAR dataset with the Reporter Panel using unique reporter IDs creates the final dataset. On average, the HMDA panel includes 8,127 mortgage reporters annually from 1990 to 2018.

Other Time Series

RMBS Issuance. Residential Mortgage Backed Security issuance volumes are sources from the Securities Industry and Financial Markets Association (SIFMA), see `https://www.sifma.org/resources/`. Agency MBS issuance volumes are obtained by adding up the dollar amount of RMBS issuance of Freddie Mac, Fannie Mae and Ginnie Mae. The volume of RMBS issuance for non-agency corresponds to private institutions other than Government Sponsored Entities.

Table 11: Description of HMDA LAR and Reporter Panel files

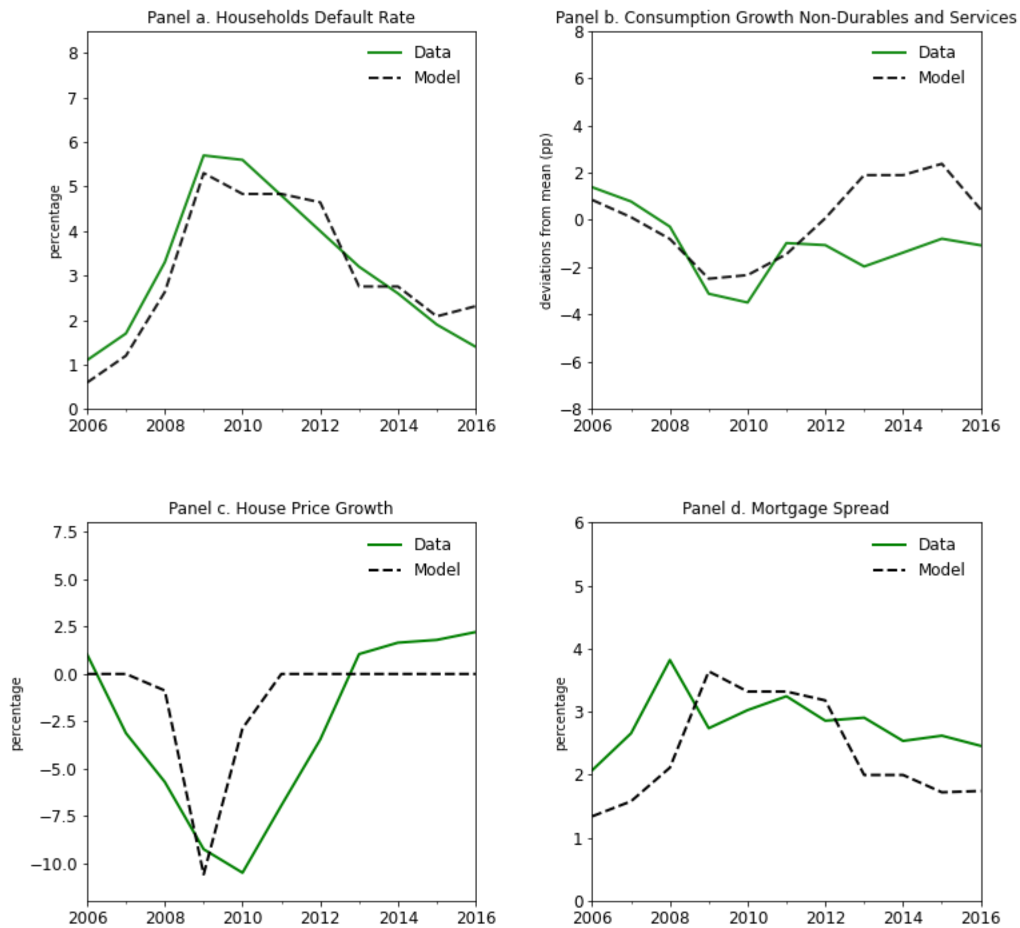
Period	File type	Observations
1990-2003	.dat	Source: https://catalog.archives.gov. See document 233.1-24ADL.pdf for a description of data-file length of fields. Starting 2004 length of fields was changed.
2004-2013	.dat	Source: https://catalog.archives.gov. For 2010 numbers coincide with tables from National Aggregates reported on FFIEC
2014-2018	.csv	Source: Consumer of Finance Protection Bureau. https://www.consumerfinance.gov/data-research/hmda/

Household Income, measured as the filtered Hodrick-Prescott cyclical component of GDP; *Default Rates*, based on the national delinquency rate for mortgage loans 90+ days delinquent or in foreclosure (source: NMDB); *Mortgage Interest Rates*, using the average 30-year fixed rate from Freddie Mac's 2018 Primary Mortgage Market Survey; and *Guarantee Fees*, from Fannie Mae and Freddie Mac Single-Family Guarantee Fee Reports by the FHFA, available at FHFA Reports (https://www.fhfa.gov/AboutUs/Reports).

E Simulations of the Benchmark Economy

E.1 Application to the Great Financial Crisis. Additional variables

Figure 14: Households Aggregates during the Great Financial Crises



Panel a. *Data* corresponds to the 90 days or more, or in foreclosure, deliquency rate for residential mortgages. Source: NMDB. Panel b. *Data* corresponds to the de-meaned growth rate of aggregate consumption of non-durable goods and services. Source: NIPA. Panel c. *Data* is the growth rate of the all-transactions house price index. Source: FHFA. Panel d. *Data* is the spread between the 30 year fixed rate mortgage and the 10 year Treasury bill. All variables are in annual frequency.

E.2 Welfare analysis

Table 12: Welfare Changes in Consumption Equivalent Units

Description	Post-GFC	Post GFC + Break-even fee
Borrowers	-0.318	-0.535
Lenders	-0.120	-0.090

All numbers are in percentage points. Welfare measures correspond to the consumption equivalent units a borrower is willing to sacrifice at the benchmark to be indifferent under the alternative economy. Negative numbers represent welfare gains.

F Quantifying Information Frictions

In this section, we design a comparable complete information economy featuring similar distortions and government policies as the asymmetric information one. Then, we use this alternative economy as a benchmark to measure the role of information frictions in amplifying the effects of income and housing shocks.[39]

A complete information economy with a distortionary wedge. In our setup, information frictions generate a wedge between the return obtained by security buyers and the return given up by loan sellers in the securitization market.[40] Such a wedge is represented by the area between equilibrium cut-offs $\{z^S, z^B\}$ in Figure 2. Hence, we conceptualize a complete information economy facing the same government policies, the same liquidity frictions, and an information-wedge (akin to a tax on security purchases) that distorts lenders' decisions. Let $\varphi(X) > 1$ be such wedge in every aggregate state of the economy X. The resources collected from this wedge are redistributed among all lenders proportionally to their portfolio size through transfers $T^{\varphi}b$. The recursive problem of a lender in this alternative economy is:

[39] In Section 2, we showed that in a complete information economy, the securitization market does not experience adverse selection, and there is no need for credit guarantees or charging origination fees on lenders. Such an economy may not serve as an appropriate counterpart to study the role of information frictions since it overlooks distortions in lenders' decisions introduced by government policy.

[40] The idea of mapping economic frictions to wedges was developed by Chari et al. (2007) to study business cycle fluctuations in a prototype growth model. Kurlat (2013) adapts the same idea to map information frictions in a model of asset creation and reallocation.

$$
\begin{aligned}
V(b,z;X) &= \max_{\{c,n,b',d,s_h,s_\ell\}} \left[u(c) + \beta^L \mathbb{E}_{X'} V(b', z', X')|X\right] \qquad (29)\\
s.t. & \\
c + n(zq+\gamma) + pd(1-\tau)\varphi &\leq ((1-x_\ell)b - s_h)\, m_h + x_\ell b m_\ell + p s_h + d_t m_d \varphi - T^L b + T^\varphi b\\
b' &= (1-\phi)\left((1-x_\ell)b - s_h + x_\ell b(1-\rho) + d\right) + n\\
& n \geq 0 \quad d \geq 0\\
& s_h \in [0, (1-x_\ell b]
\end{aligned}
$$

Notice that government policy $\{\tau, \gamma\}$ in the securitization market is exogenous. For consistency, we assume that lenders simply keep their low-quality loans as those now are publicly identified by every lender in this complete information economy.

The equilibrium allocations that solve the problem in (29) can be characterized following the same strategy presented in Section section-characterizing-quant-model. Similar to the asymmetric information problem, lenders are split into three groups according to two cut-offs given by: $\left\{\tilde{z}^S, \tilde{z}^B\right\} \equiv \left\{\frac{1}{q}\frac{p-m_h}{(1-\phi)} - \frac{\gamma}{q}, \frac{1}{q}\frac{(p(1-\tau)-m_d)\varphi}{(1-\phi)} - \frac{\gamma}{q}\right\}$.

Equivalence with an asymmetric information economy. The recursive problem of a lender in a complete information economy facing the wedge $\varphi_t \equiv \frac{1}{1-\mu_t}$ is equivalent to the problem it faces in the asymmetric information economy presented in (17). Start by conjecturing that prices $\{p_t, q_t\}$ coincide in the asymmetric-information economy and the complete information economy with the information-wedge. Since government policy is kept fixed in both economies, it must be that the first cut-off $z^S_t \equiv \frac{1}{q_t}\frac{p_t - m_{ht}}{(1-\phi_t)} - \frac{\gamma_t}{q_t} \equiv \tilde{z}^S_t$ is the same in both economies. Furthermore, whenever the information-wedge $\varphi = \frac{1}{1-\mu^*_t}$ where μ^*_t is the equilibrium value of the asymmetric information economy, the second equilibrium cut-off of both economies also coincides. Thus, the level of distortions faced by both economies in the securitization market is the same.

Shock decomposition with information frictions. The main idea of our decomposition is to isolate the impact of information frictions in the transmission of shocks by performing a comparative analysis between the economy with an endogenous wedge—arising from information frictions—and the alternative economy with complete information and a fixed wedge.

First, we simulate the benchmark economy with information frictions for $T = 100,000$ periods. Then, using the simulated allocations and prices, we compute the average information friction wedge $\bar{\varphi} = \sum_{t=1}^{T} \frac{1}{T}\varphi_t$, and the average value of the guarantee policy $\bar{\tau} = \sum_{t=1}^{T} \frac{1}{T}\tau_t$. These estimates are introduced in the comparable complete information economy so that it faces, on average, similar distortions over time. It is important to note that the comparable complete information economy shares the exact calibration as the benchmark economy with information frictions. Then, we simulate both economies for the identical sequences of income and housing volatility shocks presented in Figure 13. Figure 6 shows the dynamic responses of aggregate credit and securitization volumes from each economy compared to their data counterparts.

Table 3 summarizes the average contraction predicted by each economy for aggregate credit and securitization volumes for the period 2008 to 2013. On average, the benchmark economy with private information fits the data better than the comparable complete information economy. We estimate that information frictions multiplier of 1.2 for the credit contraction and a multiplier of 1.4 for the contraction in security issuance during the GFC. These multipliers rise as the probability that a lender privately identifies non-performing low-quality loans increases. For instance, an economy where lenders can perfectly identify all low-quality loans that will fail to perform can be replicated by setting $\rho = 1$ in our benchmark economy. Such an environment generates larger amplification effects from information frictions; repeating the above exercise yields multipliers of 1.3 for the credit contraction and 1.7 for the securities contraction during the GFC.