Mortgage Securitization and Information Frictions in General Equilibrium

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Abstract

We develop a quantitative general equilibrium model of the U.S. mortgage market where securitization, as a technology, links the credit and asset-backed security markets. Heterogeneous lenders trade in a securitization market subject to adverse selection: originators are privately informed about loan quality, while buyers anticipate a higher share of low-quality loans when household defaults rise. This friction generates an information-friction multiplier: a feedback loop where surges in household defaults drive down security prices, reduce lender liquidity, and contract mortgage credit supply. Applied to the Global Financial Crisis (GFC), the model reproduces two-thirds of the observed contraction in mortgage credit and the collapse of mortgage-backed security issuance, with information frictions amplifying the credit contraction by a factor of roughly 1.2. We use the framework to evaluate post-GFC credit guarantee policies. Post-GFC pricing stabilizes credit but generates a fiscal deficit. Pricing guarantees to reflect the amplification effects of information frictions eliminates the deficit and delivers welfare gains for both borrowers and lenders.

Keywords: Credit intermediation, mortgage markets, adverse selection, DSGE, private information, liquidity frictions.

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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, on average 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, as observed during the credit cycle of the 2000s, disrupting mortgage credit availability—a key macroeconomic variable and a policy objective.

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] This paper fills these gaps by developing a quantitative general equilibrium model of the U.S. housing-mortgage market where securitization, as a technology, shapes households' access to mortgage credit and housing. Our model generates consistent predictions for the long-term behavior of mortgage rates, credit growth, and house prices following the development of securitization. When applied to the Global Financial Crisis (GFC), it replicates two-thirds of the contraction in aggregate residential mortgage credit and the full contraction in mortgage-backed security issuance volumes observed during the bust. How important were information frictions in accounting for these dynamics? Our estimates indicate a multiplier of around 1.2, implying that information frictions played a significant role in amplifying the effects of negative household income and housing shocks on mortgage aggregates during the GFC. We then evaluate credit guarantee policies in the mortgage market and show that this information-friction multiplier has implications for the pricing of guarantees, government finances, and households' welfare.

To gain intuition for the main mechanism behind the quantitative model, we first introduce a stylized model of credit intermediation in which lenders face idiosyncratic risk in their loan origination costs and aggregate default on their legacy loans. We extend this setup to include a securities market where lenders can trade, by selling their loan portfolio or buying securities, à la Kurlat (2013). By design, the model establishes an equilibrium connection between the credit and the security markets. Differences in loan origination costs and limited liquidity incentivize lenders to participate in the security market. Lenders with low origination costs raise liquidity by selling their legacy loans,

[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 shown how such frictions can lead to sharp declines or even collapses in security trading.

and use these funds to originate new ones. In contrast, lenders with high origination costs retain their loans and invest by purchasing securities. Without information frictions, securitization allows lenders with varying liquidity needs to reallocate legacy loans, directing liquidity to the lowest-cost lenders. In equilibrium, such reallocation improves the efficiency of credit funding, lowers lending rates, and increases credit.

While this framework is parsimonious and delivers predictions consistent with long-term patterns in borrowing costs and credit supply, it also predicts that security prices are unaffected by spikes in mortgage defaults, failing to account for the positive correlation between security issuance and credit volumes observed in the data (see Figure 1 in Section 1.1). 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. This feature reconciles the predictions of our stylized model with the data, generating simultaneous contractions in both security and credit markets when the loan default rate increases. We argue that this is an essential mechanism to account for the sharp nonlinear contractions observed in both mortgage credit and residential MBS volumes during the bust phase of the GFC.

To quantify the impact of securitization frictions on aggregate mortgage credit and household aggregates, we extend the stylized framework into a quantitative general equilibrium model. This model incorporates endogenous credit demand, similar to standard macro-housing models with collateral constraints and long-term debt: 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 generates credit cycles driven by household income and housing risks. Persistent adverse income or housing volatility shocks can trigger a surge in mortgage defaults, changing 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 credit cycles. In equilibrium, information frictions amplify the aggregate effects of negative household shocks; we call this the *information-friction multiplier*.[2]

A quantitative test of the model shows it can replicate the dynamics observed during the GFC bust. From 2008 to 2013, mortgage credit contracted by 40%, while residential MBS issuance declined by 30%, as shown in Figure 1. When households experience income shocks such as those in the data, along with a sequence of housing volatility shocks that reproduce the mortgage default patterns observed during this period, the model reproduces two-thirds of the contraction in mortgage credit and the entire contraction in MBS issuance. Compared to a counterfactual economy without information frictions, our model predicts a 17% stronger decline in mortgage lending during this period. Two aspects of the data determine the magnitude of this multiplier: (i) lenders' high reliance on securitization liquidity; and (ii) the cross-sectional moments of the distribution of mortgage lending, both of which the model internally matches. Our analysis contributes to understanding the dynamics driving the GFC, showing how problems in the securitization market can spill over into the credit market and shape mortgage credit fluctuations.

We use our model to study the aggregate implications of information frictions for the design of mortgage policy. We model the government as offering a credit guarantee that compensates buyers of mortgage-backed securities for the losses associated with household default, financed by charging loan originators a fee, known as the *guarantee fee*. Any deficit from the policy is financed with lump-sum taxes on all households. The policy aims to stabilize the demand for securities, thereby expanding securitization activity and the volume of credit intermediated to households. This setup mirrors the role played by Government-Sponsored Enterprises (GSEs) in the U.S. mortgage market.[3]

Our main policy exercise contrasts the post-GFC economy, in which all MBSs carry credit guarantees and guarantee fees have tripled relative to pre-GFC levels, with a counterfactual economy in which fees are set to a break-even level that eliminates the fiscal deficit generated by the policy. We find that the post-GFC policy sustains the flow of mortgage credit and stabilizes securitization volumes, yet it does so at the cost of a persistent government deficit. Aligning guarantee fees with their break-even level lowers mortgage defaults, reduces housing equity losses, and removes the fiscal burden on households—delivering welfare gains for both borrowers and lenders. Our results indicate that pricing credit guarantees to reflect the amplification effects of information frictions can turn a fiscally costly stabilization tool into one that is Pareto-improving.

Layout. The rest of this introduction reviews 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 underlying the quantitative model introduced in Section 3. Section 5 presents the quantitative analyses, and Section 6 concludes.

[2] This multiplier is akin to Bernanke and Gertler (1989) and Bernanke et al. (1996)'s *financial accelerator*, which results from endogenous changes over the business cycle in the agency cost of lending.

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

Related Literature. This paper contributes to the literature that incorporates financial frictions into housing macro 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] By introducing securitization as a key liquidity source, our model provides a microfounded mechanism for Justiniano et al. (2019)'s relaxation and tightening of lending constraints, predicting that access to securitization expands credit supply and lowers mortgage interest costs, with significant effects on credit and house prices.

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 these models that treat asset quality as exogenous.[6] Our work also shares elements present in theoretical models (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 worsen borrowers' balance sheet, 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

[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. Shimer (2014) reviews private information in the MBS market in detail.

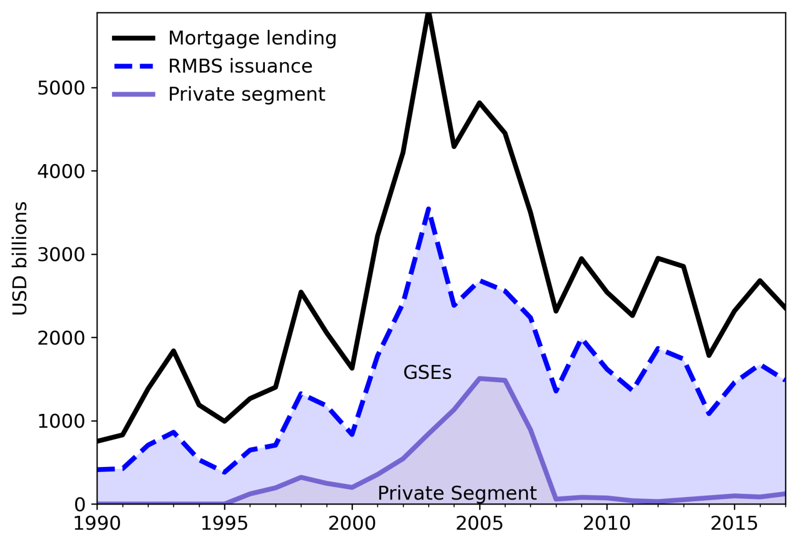
[6] Vanasco (2017) and Caramp (2019) study the interplay of endogenous asset quality production and adverse selection in secondary markets.

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 with frictions in securitization.

1.1 Institutional Features of the U.S. Mortgage Market

Securitization allows lenders to diversify their exposure to borrowers' default risk and reduce cash-flow risk by spreading these risks 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.

Figure 1: Credit and securitization mortgage markets



Notes: Mortgage lending is the aggregate volume of the flow of mortgage issuance during the first year of origination across all reporter institutions in the Home Mortgage Disclosure Act (HMDA) database. Residential Mortgage-Backed Securities (RMBS) issuance is from the Securities Industry and Financial Markets Association (SIFMA). GSEs refers to the RMBS issuance by Freddie Mac and Fannie Mae, the Government-Sponsored Enterprises. Private segment refers to the issuance by private institutions. Amounts are in USD real terms, base year 2015.

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 MBS 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;

[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.

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 important differences between MBSs issued by GSEs and by private securitizers. Among them, the most distinctive feature is that GSE-issued MBSs carry a credit guarantee that ensures principal and interest payments to investors in the event of borrower defaults, whereas private-label MBSs lack government guarantees.[8] This feature has been central in sustaining issuance in the GSE segment, 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, MBS issuance by GSEs remained substantial following the GFC. Our quantitative analysis in Section 5 accommodates this important aspect 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 5.3, we consider a fully 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 stylized two-period model of financial intermediation that can be solved by hand. We use it to highlight the securitization market's role and its link with credit-market outcomes, and to explain the main mechanism of the quantitative model in Section 3.

Environment. Consider an economy populated by a representative borrower and a continuum of risk-neutral savers, called lenders henceforth, operating in a credit market across two periods: $t = 0, 1$. In period 0, lenders use their resources to originate loans, while in period 1, they consume all their accumulated wealth. Lenders 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 the borrower, maturing in period 1. The lender also draws a stochastic cost z^j for originating new loans n^j. This idiosyncratic origination cost is distributed identically and independently (i.i.d.) across lenders with cumulative distribution function $F(z)$ with 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

[8] Other key dimensions include issuance criteria and the risk profile of the underlying mortgages. In particular, GSE-issued MBSs are backed by mortgages that comply with stricter issuance guidelines, resulting in a lower-risk pool and generally offering lower interest rates to investors, which reflects their status as low-risk, highly liquid assets. See Vickery and Wright (2013) for an in-depth analysis.

[9] We interpret z as representing heterogeneity in loan underwriting, screening, and lending opportunities across loan originators. This approach is analogous to Kiyotaki and Moore (2005) and Kurlat (2013)'s random arrival of

price of new loans, which lenders take as given since they are assumed to operate in a perfectly competitive credit market. Legacy assets are subject to the aggregate default rate: a fraction $\lambda \in (0,1)$ defaults and pays nothing at $t = 1$. Each lender holds a diversified legacy portfolio similarly exposed to aggregate default; hence, default effectively splits a lender's portfolio into a performing and a 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, and $\epsilon > 0$ governs the elasticity of credit demand.

Lending without securitization. In this environment, loan origination through z is the only technology for 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. The solution is straightforward: each lender invests through her lending technology, originating $n^j = \frac{w}{z^j q}$ based on her cost z^j. Aggregate credit supply is determined by integrating individual lending decisions across all lenders: $N^S(q) = \int_{\underline{z}}^{\bar{z}} \frac{w}{zq}\, \mathrm{d}F(z)$. Aggregate credit supply is limited by the liquid funds available to lenders, given by their cash endowment. From the credit market clearing condition for new loans $N^D(q) = N^S(q)$, we obtain the equilibrium price of credit:

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

where q^{NS} denotes the discounted price in an economy with no access to securitization (NS). As each lender operates her lending technology, the price of credit depends on the average origination cost across all lenders. The gross lending rate R for borrowers is directly linked to this cost, given by $R = \frac{1}{q}$. Higher origination costs result in higher lending rates. 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 others 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 partially relax capital market incompleteness by introducing a securities market where lenders can sell legacy loans and buy securities. Our approach to modeling security trading builds on Kurlat (2013)'s theory of asset creation and reallocation, where traders have asymmetric information about the quality of traded assets. To

investment opportunities, as well as Boissay et al. (2016)'s heterogeneous intermediation costs proportional to loan returns.

develop intuition, we first extend the credit model to include a securities market operating under complete information (CI) about the quality of traded loans, meaning that all lenders can perfectly distinguish a traded loan's quality (performing or non-performing). In this scenario, non-performing loans are either publicly identified (and not traded) or traded at a price of zero. The securities market's primary role is to transform illiquid legacy loans into homogeneous securities that can be transferred and accumulated. A security represents a 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: $\max_{\{n,d,s\}} c_1 \quad \text{s.t} \quad z^j n^j q + pd^j = w + ps^j$ as detailed in Appendix C.1. Their trading decisions result from comparing their origination cost z^j to an endogenous market cut-off z^{CI}, which, in equilibrium, is determined by the ratio of the securities 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 those with $z^j > z^{CI}$ retain their legacy loans, purchase securities, and originate zero new loans. This characterization generates two groups of lenders in the securitization market: lenders-sellers and lenders-buyers.

The securitization technology allows lenders with heterogeneous valuations of their legacy portfolio—driven by their origination cost—to benefit from trading legacy loans. Low-cost lenders sell their legacy portfolios to convert illiquid assets into liquid funds, as they can originate new loans at a lower cost. Conversely, high-cost lenders, who place a higher valuation on their legacy portfolios, retain them. For these lenders, originating new loans is costlier than investing in securities, so they opt to buy securities as an alternative. In essence, securitization improves the efficiency of credit funding by reallocating illiquid assets to those who value them most and channeling liquidity to the most efficient, low-cost lenders—capturing the core of the securitization liquidity channel.

Next, we examine how access to securitization affects prices and quantities in the credit market. The stylized model's tractable structure allows us to derive analytical expressions 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 for 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

$N^S(p,q) = \int_{\underline{z}}^{\frac{p}{q}} n(z)\ \mathrm{d}F(z) = \int_{\underline{z}}^{\frac{p}{q}} \frac{w+p(1-\lambda)b_0}{zq}\ \mathrm{d}F(z)$. 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) captures the equilibrium link between the securitization and credit markets, highlighting their joint price determination. By explicitly modeling this connection, our framework shows how allocative efficiency gains from securitization increase aggregate credit supply and reduce credit intermediation costs. In equilibrium, only the lowest-cost lenders originate new loans, resulting in a more favorable credit price for borrowers compared to a setting without 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. The price of credit satisfies* $q^{CI} > q^{NS}$.

While this model is parsimonious and delivers predictions consistent with long-term patterns in borrowing costs and credit supply, it also predicts that security prices are unaffected by spikes in the borrower default rate (see Figure 3 below), failing to account for the positive correlation between securitization and credit volumes observed in the data, as shown in Figure 1. Next, we introduce private information about loan quality, which leads to adverse selection in securitization, and ensures that securitization volumes move in tandem with lending volumes. This feature reconciles the predictions of our stylized model with the data, generating simultaneous contractions in both securitization and lending volumes when the loan default rate increases—a key prediction evident in Figure 3.

Lending with securitization and private information. We now introduce private information among lenders by assuming that, at the beginning of period $t = 0$, each lender can privately predict and identify the fraction of loans that will become non-performing in her legacy portfolio. This creates an information asymmetry that resolves by the end of the period, at which point the holders of non-performing loans recover nothing.[11] The securitization market operates as before, allowing lenders to sell legacy loans or buy securities at a pooling price $p > 0$. However, because of private information, lenders can now selectively sell loans: s_H represents sales of high-quality loans (those

[10] See Appendix C.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.

[11] In the quantitative model, which aims to represent mortgage loans, these assumptions are relaxed in two ways: first, lenders predict and identify non-performing loans imperfectly, and second, defaulting loans have a positive recovery value through the foreclosure of the loan's collateral.

that are likely to perform), and s_L denotes sales of low-quality loans (those likely to default). 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, represented by the function $\mu(p, q)$:

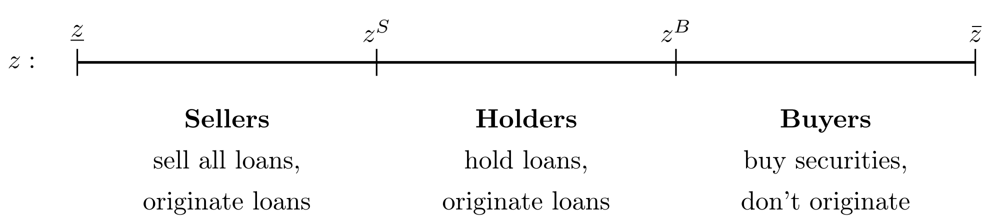
$$\mu(p, q) = \frac{S_L}{S(p, q)}, \tag{7}$$

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

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

The characterization of lenders' trading decisions $\{n, d, s_H, s_L\}$ is similar to the previous setup; see Appendix C.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 the 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, do not 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 do not originate new loans. Lenders with $z \in \left[z^S,\ z^B\right]$ retain their high-quality legacy, do not buy securities, and originate new loans. Hence, lenders self-classify into lender-sellers, lender-buyers, and lender-holders, respectively.

Figure 2: Lenders' trading groups with private information



When lenders have private information about the quality of their legacy assets, an adverse selection problem arises in the securitization market, as in Akerlof (1970). All lenders prioritize selling their low-quality loans first, and only lender-sellers also sell high-quality loans, which lowers 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 becomes $p/(1-\mu)$. This distortion discourages some lenders from selling high-quality loans and purchasing securities, disrupting the allocative efficiency of securitization. Consequently, intermediation costs rise, aggregate liquidity for new credit decreases, and lending rates are higher than they would be in the absence of information frictions.

Kurlat (2013) shows that, due to adverse selection, the securities market may collapse or become inactive if the traded fraction of low-quality assets is too high.[12] An inactive securitization market means that no positive price can clear supply and demand. In this case, the credit market still operates, but aggregate credit supply is determined only by the decisions of lenders who originate new loans using their drawn origination technology, as in the model without securitization. Hence, credit supply becomes contingent on whether the securitization market is active or inactive. Proposition 2 summarizes this result. As before, we derive analytical expressions for trading policies and the aggregates in each market; see Appendix C.4 for details. Equilibrium prices (p, q) are determined by solving the joint system of equations, based on the clearing conditions of the credit and securitization markets, similar to the system in equations (5)-(4).

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

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

where $z^B = \frac{p/q}{1-\mu(p,q)}$ *is the 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 outcome.*

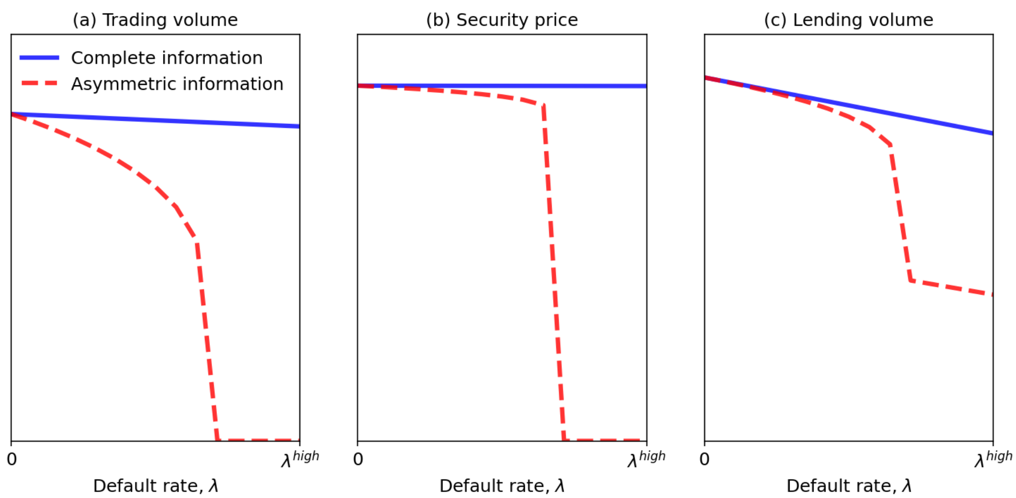
Comparative Statics. A key feature of our model is the endogenous response of the distortionary wedge to changes in the lenders' portfolio default rate (λ). In this section, we examine how a gradual increase in default rates amplifies the response of market aggregates in an economy with information frictions compared to one with complete information. Figure 3 illustrates this by simulating both economies under the same sequence of loan portfolio default rates: Panel (a) shows that as the fraction of defaulting loans increases, the volume of securities traded declines much more sharply in an economy with information frictions.[13] Security prices, shown in Panel (b), follow a similar trend:

[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)).

[13] For illustrative purposes, all responses in the figure are computed as relative ratios with respect to the economy with zero portfolio default, which is why the lines intersect at zero. For these simulations, we set $\{w_0 = 2.5, b_0 = 5, \epsilon = 0.03\}$ and set the demand shifter Θ to match a target reference rate of 3% in the frictionless credit market. For the lending technology $F(z)$ we choose a Beta distribution with support $[0.7, 1.7]$, and shape parameters $\{\alpha, \beta\} = \{7.6, 6.0\}$.

higher default rates lead to a higher proportion of low-quality loans in the securitized pool, driving up the real cost of purchasing securities and reducing demand. Consequently, the securities price that clears the market falls. In contrast, in the absence of information frictions, low-quality loans are not traded, and the price of securities remains unaffected by loan default. The discontinuity in trading volume and security price marks the threshold in the default rate beyond which the securitization market becomes inactive. Due to the equilibrium connection between the two markets, a lower securitization volume reduces liquidity available for new lending. Moreover, lending volumes exhibit a non-linear response, with a shutdown of securitization triggering even stronger reductions in lending, thereby amplifying the contraction of credit, as shown in Panel (c).

Figure 3: Amplification effect of information frictions



Notes: Simulations from the stylized model. The figures compare aggregate trading volume, security prices, and aggregate lending volume across economies with and without information frictions in the security market. The lines represent the steady-state values obtained from simulating the economies for a sequence of portfolio default rates (λ).

Up to this point, we have shown how information frictions amplify the response of aggregates in the credit and securitization markets when loan default rates are high in a stylized model. In Section 3, we extend this framework by modeling mortgage credit demand in detail, incorporating income and housing risks that affect borrowers' credit and default decisions, as well as key features of mortgage contracts. In the quantitative model, we show that a *financial accelerator* effect emerges once borrowers' credit demand and default decisions are endogenous, and cross-sectional data on 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.

3.1 Agents, Endowments, Preferences, and Markets

Agents and Preferences. Time is discrete and infinite. The model is an exchange economy with two types of agents: a continuum of lenders indexed by $j \in [0,1]$ and a borrower household with a continuum of members, indexed by $i \in [0,1]$, that enjoy perfect risk sharing.[14] Agents differ in their preferences in two dimensions. First, the borrower household (B) discounts the future more heavily than lenders (L), with $\beta^B < \beta^L$. Second, borrowers derive utility from housing services and non-durable consumption C_t, with preferences given by $U(C_t, H_t) = (1-\theta)\log C_t + \theta \log(\zeta^H H_t)$, where θ represents the valuation of housing services relative to other non-housing consumption goods, and ζ^H is the rate of conversion of housing stock to housing services. Lenders have log-preferences only over the non-durable good, $u(c_t^j) = \log c_t^j$.

Endowments. Each period, the borrower household receives a stochastic income endowment Y_t, which follows a first-order autoregressive process and is an exogenous aggregate state of the economy. Borrowers own a stock of housing H_t and mortgage debt B_t. Given our household construct, we assume that members own the same amount of housing stock h_t such that $\int_0^1 h_t di = H_t$ and the same stock of mortgage debt (liabilities) b_t such that $\int_0^1 b_t di = B_t$. Lenders' assets are given by their ownership of the borrowers' debt: b_t^j denotes the lender j's stock of mortgage loans. Each lender holds a diversified portfolio of loans distributed across household members. Lenders represent financial companies with limited access to debt markets, relying primarily on private equity for funding.[15]

Markets. The economy features three types of assets traded in distinct markets. The housing market is segmented, with borrower households buying and selling housing units, while lenders only sell foreclosed properties.[16] In the credit market, borrowers and lenders exchange resources through long-term mortgage loans collateralized by housing. The third asset is a mortgage-backed security, which bundles 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.
Next, we describe the borrower's and lenders' problems in detail.

[14] The household construct allows us to model partial default tractably (Elenev et al. (2016); Faria-e Castro (2022)).

[15] Our setup captures relevant features of a large fraction of mortgage originators operating with limited funding and acting as financially constrained intermediaries (Loutskina and Strahan (2009); Loutskina (2011)).

[16] Our assumption is convenient for two reasons. First, it aligns with empirical evidence from Landvoigt et al. (2015), who show significant segmentation in housing markets between wealthy (lender) and non-wealthy (borrower) agents. They also find that, during the boom-bust period, house prices were primarily driven by the lower end of the price distribution, where borrowers are more credit-constrained, consistent with our approach. Second, it lends tractability to our framework, and it is equivalent to assuming rigid housing demand from lenders (Greenwald (2016); Elenev et al. (2016); Justiniano et al. (2019); Faria-e Castro (2022)).

3.2 Borrower's Problem

Mortgages and Housing. Mortgages are long-term loans subject to default and prepayment. The loan contract is characterized by (δ, κ): $\delta \in (0,1)$ is the mortgage (inverse) duration, and $\kappa > 0$ is the coupon on the outstanding principal.[17] To finance house purchases, the household takes on long-term mortgages extended by lenders. New mortgages N_t are priced competitively at the discounted price q_t. Housing units are traded at a price p_t^H. For tractability, the housing supply is fixed at $\bar{H}$, which implies that houses are priced by borrowers.

Default and Foreclosure. Household members experience housing valuation shocks ω_t^i with cumulative distribution function (CDF) $G_\omega(\mu_\omega, \sigma^2_{\omega_t})$, 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 housing volatility aggregate state. Appendix G.3 shows that the default rate at the household level is characterized by an endogenous threshold $\bar{\omega}_t$, such that only members with $\omega_t^i \leq \bar{\omega}_t$ default on their mortgages. The aggregate default rate is defined as $\lambda(\bar{\omega}_t) = \Pr[\omega_t^i \leq \bar{\omega}_t]$. Upon borrowers' default, lenders foreclose on the housing collateral, recovering only a fraction $\psi \in [0,1)$ of its market value—foreclosed houses sell at a discount due to rapid liquidation by financial institutions (Campbell et al. (2011)). $\Psi_t(\bar{\omega}_t) = \psi \mathbb{E}[\omega_t^i | \omega_t^i < \bar{\omega}_t] \frac{p_t^H H_t}{B_t}$ represents the recovery function per unit of debt; the conditional expectation reflects the average quality of foreclosed houses.

Prepayment. After default, 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.[18] Given the mortgage contract structure, the effective amortization (maturity) rate after accounting for prepayments is $\phi_t = \delta(1-\eta_t)+\eta_t$. Total mortgage payments per unit of debt, comprising amortized principal and coupon payments, are $m_t = \phi_t + \kappa(1-\phi_t)$.

Recursive Problem. The borrower household solves:

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

[17] This structure reflects key features of 30-year fixed-rate mortgages. Following Chatterjee and Eyigungor (2015); Elenev et al. (2016), we model mortgages as perpetuities with declining principal balances, allowing borrower equity to build over time. A fixed duration δ avoids tracking loans of varying vintages while capturing the dynamics of aggregate mortgage cash flows for lenders.

[18] 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 are tied to income, employment, and housing shocks.

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 the left side of the household's budget constraint (11) includes expenses in consumption, housing purchases, and housing transaction costs (Piazzesi and Schneider (2016)) with $\Xi_{H,t} = p_t^H H_{t+1}\frac{\nu}{2}(\frac{p_{t+1}^H H_{t+1}}{p_t^H H_t} - 1)^2$, 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 holdings, where $\mu_\omega(\bar{\omega}_t) = \mathbb{E}[\omega_t^i \mid \omega_t^i \geq \bar{\omega}]$ is the conditional value among members who avoid default; new mortgage credit $q_t N_t$; and income endowment Y_t. X_t is a vector of exogenous states to be explained below.

The law of motion for mortgage debt in (12) consists of two parts: the total outstanding mortgage debt net of default and newly originated mortgages. Default impacts household finances by reducing outstanding liabilities and mortgage payments, but it also lowers the housing stock. The household also faces a borrowing constraint (13)—limiting end-of-period debt B_{t+1} to a fraction π of the next period's market value of housing. π reflects the loan-to-value (LTV) regulatory limit.

3.3 Lenders' Problem

Loan 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 $[\underline{z}, \bar{z}] \in \mathbb{R}_+$. 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.

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.[19] This feature generates different expected cash flows according to the mortgage quality; 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. High-quality mortgages pay $m_{ht} = m_t$. Lenders predict the aggregate default rate and use it to infer $x_{\ell t}^j$ according to the following relation:

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

[19] 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.

which indicates that each lender's expected portfolio default rate aligns with the aggregate rate, consistent with lenders diversifying across borrowers. The lender's capacity to privately identify a mortgage's quality 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.[20] By the end of the period, after the household's default rate is determined, mortgages are publicly identifiable as either performing or non-performing.

Securitization Trading. Lenders participate in a securitization market à 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 $s^j_{\ell t}$ represent 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.[21] Using the notation from our stylized model, let μ_t denote the fraction of low-quality loans sold into securitization affected by borrower default:

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

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

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

where the next period's portfolio includes newly originated loans n^j_t, non-maturing ones 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.

[20]Private information about loan quality often arises during borrowers' screening: 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 observing the same data, differences in valuation models may lead to asymmetric information between parties (Shimer, 2014; Krainer and Laderman, 2014).

[21]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).

Government Policy. We capture U.S. mortgage policy in the securitization market with two instruments: a contingent subsidy for security purchases resembling a credit guarantee τ_t and a guarantee fee γ charged to lenders originating loans. The credit guarantee reflects government incentives to maintain market liquidity. The cash flow of a guaranteed MBS equals that of high-quality mortgages, $m_{gt} = m_{ht}$, shielding buyers from default risk while leaving them exposed to prepayment risk. Any deficit is financed through lump-sum taxes levied on borrowers and lenders.

Recursive Problem. A lender j maximizes:

$$V(b_t^j, z_t^j; X_t) = \max_{\{c_t^j, b_{t+1}^j, d_t^j, s_{ht}^j, s_{\ell t}^j\}} u(c_t^j) + \beta^L \mathbb{E}_{X_{t+1}|X_t} V(b_{t+1}^j, z_{t+1}^j; X_{t+1}), \tag{17}$$

subject to the law of motion of their legacy portfolio in (16) and subject to:

$$c_t^j + n_t^j(z_t^j q_t + \gamma_t) + p_t(1-\tau_t)d_t^j$$
$$\leq ((1-x_{\ell t}^j)b_t^j - s_{ht}^j)m_{ht} + (x_{\ell t}^j b_t^j - s_{\ell t}^j)m_{\ell t} + p_t(s_{ht}^j + s_{\ell t}^j) + d_t^j m_{gt} - T_t^L b_t^j, \tag{18}$$

$$s_{ht}^j \in [0,\ (1-x_{\ell t}^j)b_t^j], \tag{19}$$

$$s_{\ell t}^j \in [0,\ x_{\ell t}^j b_t^j]. \tag{20}$$

The flow of funds constraint in (18) outlines 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.[22] $p_t d_t^j$ 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, cash from loan sales $p_t(s_{ht}^j + s_{\ell t}^j)$,[23] cash from MBS purchases bearing government guarantees $d_t^j m_{gt}$, and proportional taxes. (19) and (20) represent portfolio restrictions on sales of high- and low-quality loans. New loans and security purchases are non-negative, $n_t^j \geq 0$ and $d_t^j \geq 0$.

3.4 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.4 for estimation details. $\Gamma_t(b,z)$ represents the joint cumulative distribution of lenders over the loan stocks and origination costs.[24]

[22] 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.

[23] 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 $p > \Psi(\bar{\omega})$.

[24] 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.

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 for securities is $D_t = \int d_t^j \; d\Gamma_t(b, z)$.

The government budget constraint is given by

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

On the left-hand side, $\gamma_t N_t$ represents revenues from the guarantee fee, while T_t^B and $T_t^L B_t$ are the lump-sum tax on borrowers and the proportional tax on lenders, respectively. The right-hand side comprises 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, $\Xi_{H,t}$ is the housing adjustment cost, and $\zeta_t = q_t \int (z_t^j - 1) n_t^j \; d\Gamma_t(b, z)$ is the aggregate cost of lending in the economy.

3.5 Competitive Equilibrium

A recursive competitive equilibrium given government policy $\{\gamma, \tau, T^B, T^L\}$ consists of a 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) the borrower's 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 in (21); (iv) the discounted price of lending $q > 0$ clears the credit market in (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 default rate in (14); (vii) the aggregate law of motion for $\Gamma'(b, z)$ is generated by the Markov processes of the exogenous states and the distribution of lenders' origination costs $F(z)$, and is 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.[25]

4 Calibration and Estimation

The model is calibrated at annual frequency. The reference period is 1990 to 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 National Income and Product Accounts (NIPA) data, including consumption of non-durables and services. The time discount factor for lenders, $\beta^L = 0.985$, is calibrated to match the 1.6% average real rate on 1-year Treasury bills. The housing preference parameter $\theta = 0.22$ is set to match the ratio (0.14) of the flow of residential mortgage credit—from HMDA—to the stock of residential real estate—from the U.S. Financial Accounts. The housing services parameter, $\zeta^H = 0.51$, matches average annual housing returns, 9.4%, computed using U.S. house price and rent indexes.[26] The parameter ν is calibrated to match a 3% housing moving frequency inferred from Emrath (2009). The loan-to-value ratio, $\pi = 0.80$, reflects the average LTV on first-lien mortgages across all originators from the National Mortgage Database (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 Bureau of Economic Analysis (BEA).

Mortgages and Prepayment. We model 30-year fixed-rate mortgages (FRMs) with a fixed duration parameter $\delta = 0.03$, and a coupon rate $\kappa = 0.05$, representing a standard mortgage. We let the prepayment rate, η_t, follow a stochastic process that correlates positively with household income (Appendix D.4), capturing empirical evidence that households prepay mortgages more often during favorable macroeconomic conditions (Gabaix et al., 2007). The mean prepayment rate, $\bar{\eta} = 0.12$, and its standard deviation 0.03, are consistent with historical prepayments for conventional 30-year FRMs as reported by SIFMA for the GSEs. 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)).

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

[26] We provide the formulas for housing returns, housing rents, and housing premia in Appendix D.2.

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: high and low volatility. We use the cross-sectional variance of house price growth as the data counterpart, computed from the Federal Housing Finance Agency (FHFA) house price index data, available for all 50 U.S. states from 1975 to 2020.[27] We model borrower household income, Y, using the Hodrick-Prescott (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 borrower household income into a joint first-order Markov process. 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 4.05% during crisis periods and an unconditional default rate of 2%, consistent with the national 90-days-or-more delinquency rate reported by the NMDB.[28]

Our joint income and housing volatility Markov process replicates a recession probability of 0.34, in line with the long-term frequency of recessions reported by the National Bureau of Economic Research. In 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.

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 40% in normal times and 50% 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, as reported by HMDA.

Lenders' Technology. The distribution of origination costs across lenders, $F(z)$, is modeled as a generalized Beta distribution with shape parameters (s_1, s_2). We estimate its structural parameters using a simulated method of moments, matching the model's market share for the third and fourth quartiles of the mortgage lending distribution to the data. These, along with a wider set of cross-

[27] See Appendix D.4 for details. Our approach builds on Elenev et al. (2016), who fit the dynamics of mortgage default during the 2007–2012 foreclosure crisis by calibrating a two-regime Markov process for housing volatility shocks. Unlike their work, we use publicly available house price index data to estimate the underlying process.

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

Table 1: Calibration for the baseline economy

	Description	Value	Source/Target
	Borrowers		
β^B	Borrowers discount factor	0.97	Consumption to disposable income. NIPA 90-18.
θ	Housing expenditure share	0.22	Mortgage credit to residential real estate. HMDA 90-18.
ζ^H	Housing services	0.51	Annual housing returns. Appendix C.
π	Loan to value ratio	0.80	Loan to value at origination. FHFA 90-18.
ν_1	Housing quadractic adj. costs	14.5	Housing moving frequency.
μ_ω	Mean housing valuation	0.97	Residential capital depreciation. BEA.
σ^2_ω	Variance of housing shocks	$\{0.001, 0.006\}$	Mortgage default rate in crisis times. Appendix C.
	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. Appendix C.
ϵ_η	Prepayment rate, std	0.03	Std prepayment, conv. 30-yr FRM. Appendix C.
ψ	Foreclosure recovery	$\{0.50, 0.65\}$	Mortgage severities. Appendix C.
	Lenders		
β^L	Lenders discount factor	0.985	Mean 1y Tbill real rate.
lc	Location of origination dist.	0.694	Estimated. Appendix C.
s_1	Shape origination dist.	7.55	Estimated. Appendix C.
s_2	Shape origination dist.	5.95	Estimated. Appendix C.
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, Urban Institute 90-06.
α	Securities subsidy coverage	0.60	Market share of agency MBS, SIFMA 90-06.

sectional moments, are computed in Appendix D.1 using the HMDA panel of mortgage originators covering 1990–2018. 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 matches other moments of the cross-sectional distribution of lending.

Government Policy. The government's policy instruments are $\{\gamma, \tau\}$. In the baseline 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 (Goodman et al., 2022).[29] For the coverage of credit

[29]See Appendix D.4 for the expression of γ as a function of the quoted credit guarantee in basis points.

Table 2: Targeted and Non-targeted Moments

Targeted Moments

Variable	Model	Data	Description
Borrowers			
Consumption to income ratio	0.81	0.79	Consumption to disposable income. NIPA 90-18.
Mortgage debt to housing stock	0.13	0.15	Mortgage lending to residential real estate. HMDA 90-18.
Housing moving frequency (pp)	3.00	3.00	Housing moving frequency. Emrath (2009).
Housing returns, mean (pp)	9.20	9.42	Returns to housing, 90-06. Appendix D.2
Mortgage rate spread (pp)	1.80	1.66	30y FRM spread w.r.t 10y Tbill. FRED 90-18.
Default rate - uncond. (pp)	2.01	1.99	Mortg. delinquency (90d + foreclosure). NMDB 91-18.
Default rate - crisis (pp)	4.36	4.05	Mortg. delinquency (90d + foreclosure). NMDB 07-12.
Lenders			
Fraction of loans securitized	0.71	0.70	Mortgages securitized within 1st-year. HMDA 90-18.
Severity rate - uncond. (pp)	40.69	31.99	Mean severity, mortgages w/ LTV 60-80. GSEs 99-17.
Severity rate - crisis (pp)	50.70	43.85	Mean severity, mortgages w/ LTV 60-80. GSEs 05-08.
Market share Q4	0.947	0.960	Distribution of mortgage lending (Q4). HMDA, 90-18.
Market share Q3	0.045	0.029	Distribution of mortgage lending (Q3). HMDA, 90-18.
Market share Q1	0.003	0.002	Distribution of mortgage lending (Q1). HMDA, 90-18.

Non-targeted Moments

Variable	Model	Data	Description
Default normal-times (pp)	1.82	1.20	Mortg. delinquency (90d + foreclosure). NMDB, 91-06.
Mortg. effective duration	7.25	7.50	Effective duration of 30y FRM. Walentin (2014)
Fraction of small lenders	0.83	0.91	Cross-section mortgage lenders. HMDA, 90-18.
Lending volume, top 10/bottom 90	16.09	9.19	Lending vol. top 10% / bottom 90%. HMDA, 90-18.
Correlations			
Volume security w/ lending	0.83	0.94	RMBS issuance and mortgage lending, 90-18.
Default w/ lending growth	-0.11	-0.14	Mortgage delinquency and mortgage lending growth, 90-18.
Rent growth w/ housing premium	0.45	0.29	Rent growth and housing premium, 90-18.
Rent growth w/ housing returns	0.37	0.41	Rent growth and housing returns, 90-18.

guarantees, we calibrate the baseline 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 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 baseline economy, we set $\alpha = 0.6$, consistent with the pre-GFC market share of GSE securitization.[30] In Section 5.3, where we examine the post-GFC economy, we set $\alpha = 1$ to explore the dynamics of the current securitization market. In the baseline 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 credit and securitization volumes, consistent with the data. This correlation arises from the endogenous securitization liquidity 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 correlations between housing rent growth and both the housing premium and housing returns. Additionally, Appendix D.2 shows that the model aligns well with the data by comparing other moments for housing returns, housing premia, and rent growth across several periods of interest.

5 Quantitative Analysis

5.1 An application to the Global Financial Crisis

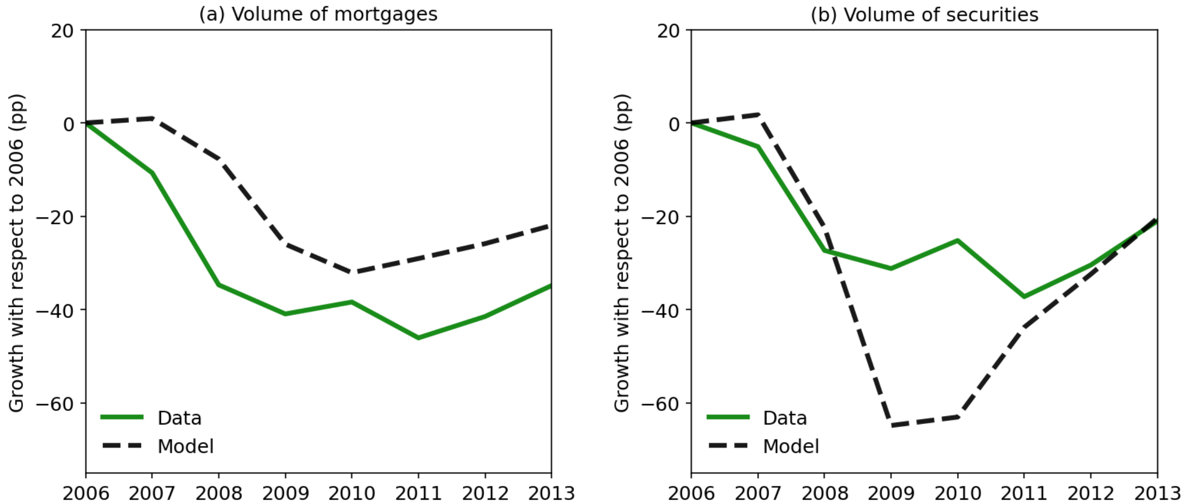
This section examines the model's predictions for aggregate outcomes in the mortgage market following the GFC. We start by asking: how much of the observed contraction in residential mortgage credit can be accounted for by disruptions in the securitization market? To address this question, we simulate the model under its baseline calibration, using a sequence of aggregate household income and housing volatility shocks that replicates the observed path of GDP and default rates from 2006 to 2013, as shown in Figure 12 in Appendix D.3.

The model accounts for two-thirds of the 40.6% average contraction in aggregate residential mortgage lending observed from 2008 to 2013. Figure 4 shows the percentage changes in the volume of the flow of mortgage lending (Panel a) and the volume of MBS issuance (Panel b) 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 on aggregates—a mechanism similar to that in our stylized framework. Beginning in 2007, the data reveal a significant decline in household income accompanied by a surge in mortgage defaults. Similarly, in the model,

[30] We focus on the aggregate securitization market, without modeling the GSE versus private market segmentation, since after 2013 the private segment shrank to less than 5% of total residential MBS issuance (Goodman et al., 2022).

Figure 4: The mortgage market during the Global Financial Crisis



Notes: All variables are expressed as two-year moving average growth rates relative to 2006. *Data* (solid green line) shows the growth of the nominal volume of the flow of mortgage issuance from HMDA (Panel a) and the growth of the nominal volume of residential mortgage-backed securities issuance from SIFMA (Panel b). *Model* (black dashed line) shows the simulated growth of the aggregate flow of mortgage lending (Panel a) and of the aggregate securitization volume (Panel b) in the baseline economy with private information.

income and housing shocks trigger a sharp rise in household default rates. As default rates rise, adverse selection in securitization leads to rapid deterioration of the average quality of traded securities. This deterioration shifts the composition of lenders—sellers, holders, and buyers—reducing demand for securities and causing securitization liquidity to dry up quickly. These effects spill over into the credit market, since mortgage originators (lender-sellers and lender-holders) rely on securitization liquidity to issue new mortgages. Strong contractions in mortgage credit occur as some of the most efficient originators—accounting for a large share of lending—switch from securitizing their entire portfolio to securitizing a small fraction. In other words, the composition of mortgage originators endogenously changes towards a larger proportion of lenders with lower cash holdings as securitization liquidity declines. In parallel, as the allocative efficiency of securitization is disrupted, intermediation costs increase, driving up mortgage rates. These supply-side forces adversely affect household access to mortgage credit, exacerbating defaults and decreasing consumption. The model predictions for other household aggregates: house price growth, the mortgage spread, and aggregate non-durable consumption are also in line with the observed dynamics in the data during this period; see Figure 9 in Appendix B.

Second, the characteristics of the cross-sectional distribution of mortgage lending play a key role in informing the model's amplification dynamics. Estimating the structural parameters governing lenders' origination costs in Section 4 reveals that a lending market dominated by a small number of lenders—accounting for a large share of total lending—corresponds to an origination cost distribution, $F(z)$, with a small mass of low-cost lenders and a large mass of high-cost lenders. This structural feature of the U.S. mortgage market is key for informing equilibrium prices and quantities. Our baseline calibration matches the average securitization fraction of the lenders' mortgage portfolios up to 2006, stressing mortgage originators' high reliance on securitization for funding.[31]

In the securitization market, the aggregate volume of MBS issuance declined by an average of 30%. Our model predicts a substantially larger average decline of 43%, with a stronger contraction in 2009 and 2010, as shown in Panel b of Figure 4. This occurs because the model does not account for the large-scale asset purchase programs conducted by the Federal Reserve and the Treasury Department during this period.[32] Naturally, as the model ignores these events, it predicts a stronger decline in security issuance.

Dynamics Across Securitization Segments. Although aggregate MBS issuance declined during this period, the performance of different securitization segments diverged significantly. Figure 5 examines the credit and securitization dynamics in a fully credit-guaranteed MBS market resembling the GSE segment and compares them to the predictions of our baseline calibration. Panel (b) illustrates that securitization liquidity exhibits a muted response to rising mortgage defaults when the securities market is fully guaranteed. Panel (a) shows that the contraction of mortgage lending is less pronounced than in the baseline economy. These dynamics align with the overall behavior of the GSE-dominated segment, where investors faced limited borrower credit risk exposure. In contrast, private (non-GSE) securitization collapsed entirely, as shown in Figure 1 in Section 1.1, given the significant pre-GFC investor exposure to mortgage defaults via private securitization. While our model does not explicitly account for market segmentation, its predictions align with aggregate market dynamics.

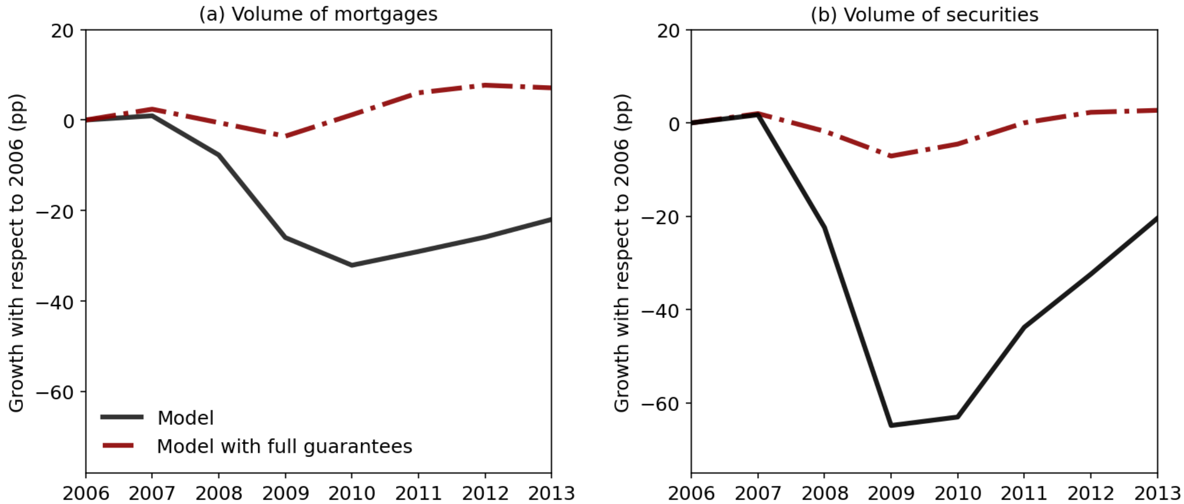
5.2 Quantifying Information Frictions

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

[31] Consistent with the mortgage funding practices of mortgage companies and large banks dominating the market, as documented by Loutskina and Strahan (2009), Stanton et al. (2014), and Jiang et al. (2020).

[32] The GSEs, Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation), incurred substantial credit losses during the financial crisis. Their securitization activities would likely have been severely disrupted without significant government interventions. Notably, the Federal Reserve and the Treasury Department implemented several large-scale asset purchase programs to sustain liquidity and credit availability in the GSE segment. 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. Additionally, the GSEs were placed under conservatorship to stabilize their operations. See Frame et al. (2015) for details on the GSEs' financial position during this period.

Figure 5: Economies with full and partial credit guarantee



Notes: All variables are expressed in growth rate with respect to 2006 with a two-year moving average window. *Model* shows the simulations from the baseline economy with partial credit guarantees where securities bear a 60% credit guarantee coverage. *Model with full guarantees* corresponds to the post-GFC economy where securities bear 100% coverage. Both economies face the same sequence of household income and housing volatility shocks.

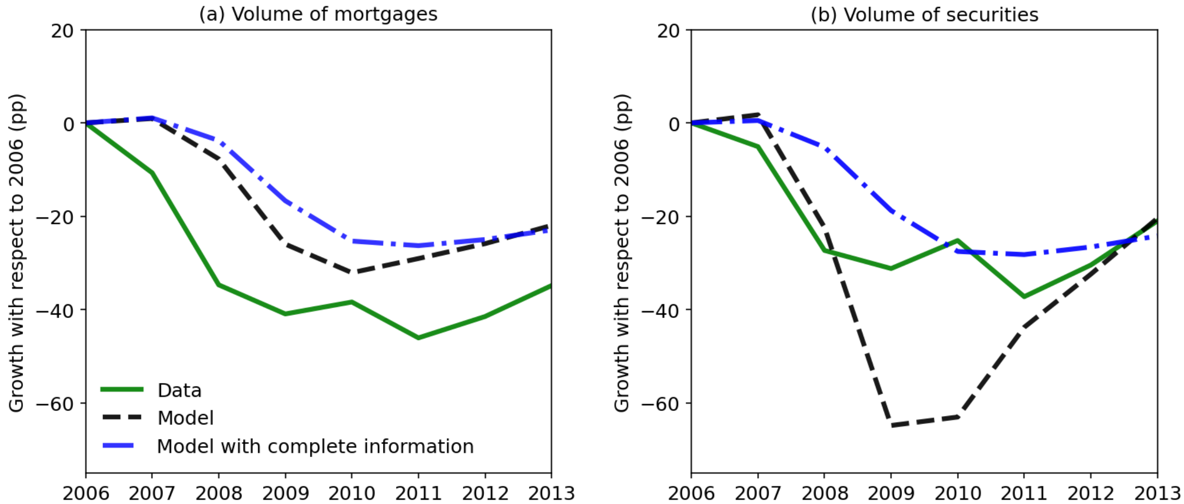
shocks? To isolate the role of information frictions in amplifying household income and housing volatility shocks, we compare simulations of the baseline model to an alternative economy without information frictions but where lenders face an equivalent distortionary wedge—labeled the *complete information economy*.[33] In this alternative setup, lenders face the same government policies, liquidity frictions, and an exogenous distortionary wedge (similar to a tax on security purchases) that affects 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. Figure 6 presents the simulations for both economies and Table 3 shows their implied average contraction in mortgage credit and securitization volumes from 2008 to 2013.

Information frictions played an important role in amplifying household shocks during the GFC. We estimate that the mortgage credit contraction was amplified by a factor of 1.2 compared with an economy without such frictions in the securitization market.[34] The multiplier is the ratio of the average contraction predicted by the baseline economy (column 2) to that of the alternative economy with complete information (column 3), as shown in Table 3.

[33]In Appendix F we explain in detail how such an alternative economy is constructed and its connection to the baseline economy.

[34]Calem et al. (2013) also document amplification effects from the securitization liquidity channel at the micro level. In particular, commercial banks highly exposed to securitization liquidity experienced a credit contraction six times greater than similar banks not dependent on securitization during the collapse of the private MBS market.

Figure 6: Quantifying information frictions during the Global Financial Crisis



Notes: All variables are expressed as two-year moving average growth rates relative to 2006. *Data* (solid green line) shows the growth of the nominal volume of the flow of mortgage issuance from HMDA (Panel a) and the growth of the nominal volume of residential mortgage-backed securities issuance from SIFMA (Panel b). *Model* (black dashed line) shows the simulated growth of the aggregate flow of mortgage lending (Panel a) and of the aggregate securitization volume (Panel b) in the baseline economy with private information. *Model with complete information* shows the respective simulations for the alternative model without information frictions.

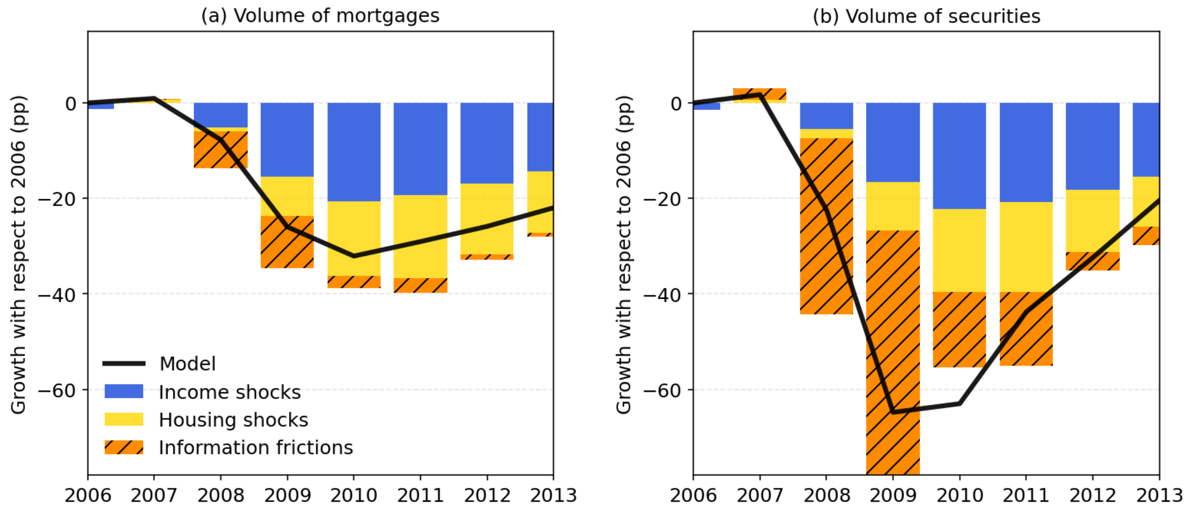
Table 3: Performance of the baseline model, 2008-13

Aggregates	Data	Baseline model	Complete information
Volume of Mortgages	-40.6	-25.7	-22.0
Volume of Securities	-29.8	-43.0	-23.7

Notes: The table reports the average contraction in aggregates from 2008 to 2013 in the data (column 1), the simulations for the baseline economy with private information (column 2), and for the alternative economy with complete information (column 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 alternative 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. The estimated effect of information frictions is depicted by the orange shaded bars. We obtain this estimate by comparing the aggregate responses between the baseline and alternative 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. Our analysis shows that information frictions amplified household shocks most strongly from 2008 to 2010, coinciding

Figure 7: Shock decomposition during the Global Financial Crisis



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

with the unexpected surge in mortgage defaults.[35]

Borrowing Costs and House Prices during Credit Expansions. We focus our analysis on aggregate dynamics during the GFC, as our framework captures how adverse household shocks can trigger significant contractions in mortgage credit through the securitization liquidity channel. The primary amplification mechanism is adverse selection in securitization, driven by the endogenous dynamics of borrowers' credit risk. In contrast, we do not address the dynamics of the 2000s housing boom, as our framework abstracts from goods production (household income is exogenous), both in the final good sector and in the housing sector, thereby missing the endogenous effects of credit expansions on aggregate output and housing supply. These factors, along with the dynamics of mortgage rates, have been shown to play a critical role in explaining the rapid growth in house prices during the 2003–2006 housing boom (Favilukis et al. (2017); Garriga et al. (2019)).

Despite the limitations of our framework on this front, in Appendix A we present an exercise illustrating that the quantitative model yields consistent predictions for borrowing costs, mortgage debt, and house prices during credit supply expansions. Specifically, we demonstrate that as securitization frictions are relaxed, lenders securitize a larger share of their mortgage portfolios. This liquidity inflow expands credit supply, making credit more accessible to credit-constrained borrowers and significantly driving house price growth. These predictions are consistent with studies highlight-

[35] These findings align with broader models examining the aggregate amplification effects of information frictions in asset markets through liquidity channels (Morris and Shin (2012); Kurlat (2013); Bigio (2015); Asriyan (2020)).

ing that credit supply-side frictions played a central role in shaping house price dynamics during the housing boom (e.g., Justiniano et al. (2019)).

5.3 Evaluating the Current Securitization Market

The Post-GFC Economy. Two significant changes reshaped the mortgage securitization market after the GFC. First, the private securitization segment collapsed, leaving only the GSE segment in place from 2008 onward. To reflect this structural shift, we set $\alpha = 1$, modeling a fully guaranteed GSE-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.[36] We incorporate these two 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 that generates sufficient revenue to fund the credit guarantee policy without incurring a deficit. Table 4 presents selected statistics from the model's simulations for two scenarios: the post-GFC economy, and a counterfactual post-GFC economy that implements the break-even guarantee fee.

Pricing Credit Guarantees. Over the past decade, a key policy focus has been ensuring that GSE credit guarantees accurately reflect borrower credit risk and fully cover the associated costs. Our analysis 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. Our model predicts a 1.5% deficit-to-GDP in the post-GFC economy, which arises solely from this policy. This raises an important question: How can the pricing of public credit guarantees on mortgages be improved?

One potential approach to improving the pricing of credit guarantees is to account for aggregate risk factors that can disrupt market functioning during times of stress. With this perspective, we estimate a break-even guarantee fee—the fee at which the policy generates no deficit. For the post-GFC economy, our estimated fee is 155 basis points. This estimate incorporates the amplification effects of information frictions, which, as we argue, are essential to account for the aggregate mortgage credit and securitization dynamics of the U.S. mortgage market.[37] Column 2 of Table 4 presents the simulated moments for the post-GFC economy with the break-even guarantee fee. Notable dif-

[36]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." The historical evolution of GSE guarantee fees is documented in the March 2022 monthly report of the Urban Institute; see Goodman et al. (2022).

[37]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	Post-GFC	Post GFC + break-even fee
Credit guarantee fee (bps)	60	155
Borrower consumption, ΔC	—	1.94
Borrower mortgage debt, ΔB	—	1.56
Default rate, unconditional	2.78	1.94
Default rate, crisis times	6.27	5.59
Mortgage spread, mean	1.09	1.38
Mortgage spread, std	1.02	1.20
Mortgage loss rates - crisis	3.12	2.79
Fraction of loans securitized	100.0	100.0
Security prices volatility	4.05	4.62
Deficit to GDP	1.47	-0.00
Prob. of market collapse	4.68	1.40

Notes: All numbers are in percentage points. Moments are obtained from simulating the baseline model (100,000 periods). Column post-GFC economy considers the policy and structural changes introduced after 2013. Column post-GFC + break-even price simulates a counterfactual economy where the guarantee fee is consistent with a zero deficit-to-GDP. ΔC and ΔB represent the average percentage change of non-durable consumption and mortgage debt, respectively, relative to the Post-GFC economy.

ferences arise when comparing the two economies. First, despite the guarantee fee increasing more than two-fold, from 60 to 155 basis points, the mortgage spread increases less than proportionally, by 27 basis points. This outcome is driven by two opposing forces: the higher guarantee fee pushes mortgage rates upward, while general equilibrium effects from reduced default risk drive down mortgage spreads because lenders face lower net mortgage losses. Since the break-even fee does not generate a deficit, households do not face additional taxes. Overall, lower deadweight losses from defaults and foreclosures, together with lower taxes, enable households to increase their consumption of non-durable goods. These effects also spill over into the securitization market, stabilizing liquidity provision and reducing the probability of market collapses.

Welfare. Table 5 evaluates welfare across different economies. The first row compares the baseline pre-GFC economy with the post-GFC economy, asking how much, in consumption-equivalent units, agents would be willing to sacrifice to move from the pre-GFC to the post-GFC economy. Our analysis shows that borrowers would rather stay in the pre-GFC economy—they experience welfare losses in the post-GFC setup, while lenders are slightly better off. This is because borrowers benefit primarily from lower mortgage rates and increased housing consumption, but in exchange, they have to pay higher taxes to finance the more stable credit and securitization markets. Lenders' welfare gains stem from improved allocative efficiency in the securitization market, which reduces intermediation costs and enhances risk-sharing.

Table 5: Welfare changes in consumption equivalent units

	Borrowers	Lenders
Pre-GFC vs Post-GFC	2.74	-0.51
Post-GFC vs Break-even fee	-2.46	-0.10

Notes: All numbers are in percentage points. Economy X vs economy Y welfare measures indicate the consumption equivalent units a borrower (or lender) in economy X is willing to sacrifice to be indifferent respect to economy Y. Positive numbers represent welfare losses. Negative numbers represent welfare gains.

The second row of Table 5 shows that the counterfactual post-GFC economy where the government deficit-to-GDP is zero generates welfare gains for all agents in the economy. In this scenario, both borrowers and lenders are better off. Borrowers' welfare gains arise from lower mortgage defaults, reduced housing equity losses, and lower taxes. For lenders, higher guarantee fees lead to lower dividend payments, even after passing some of those costs on to mortgage rates. However, the benefits of lower deadweight losses from mortgage foreclosures and a more stable securitization market outweigh the costs.

In sum, our work highlights deficiencies in the pre-GFC market's coverage and pricing of credit guarantees. Specifically, we highlight the importance of implementing a uniform level of credit guarantee coverage across MBS market segments to safeguard the financial stability of mortgage credit provision. We also emphasize the need to account for aggregate frictions in securitization when setting guarantee fees, which could generate welfare gains for all households in the economy. While our analysis is primarily positive rather than normative, it offers valuable insights into the limitations of the current market design and potential areas for improvement.

How can the design of mortgage and housing policies be further improved? Next, we discuss additional considerations about the current state of the credit guarantee policy.

A primary concern with MBS issuers offering full credit guarantees 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)). 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 current credit guarantee policy is the concentration of credit risk in a few entities. As of 2022, Fannie Mae and Freddie Mac guarantee or own $5.6 trillion in residential mortgages (as reported by the FHFA), 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 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, and the optimal equity capital structure for the GSEs.

6 Concluding Remarks

Securitization is the primary but volatile source of liquidity for U.S. mortgage lending. The GFC exposed how information frictions can drive sudden disruptions in this market. We develop a model that is consistent with the U.S. mortgage market structure and is capable of replicating these dynamics. The model stresses the equilibrium connection between securitization and the credit market through the securitization liquidity channel. It also provides a microeconomic foundation for how securitization, as a technology, improves 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 securities serves as a key source of liquidity for primary credit markets.

We use this framework to quantify the amplification effect of information frictions on aggregate mortgage credit and MBS issuance during the GFC. Our findings suggest that information frictions in securitization amplified the observed credit contraction, in line with theories stressing information-driven liquidity channels. Our work demonstrates how household shocks leading to surges in mortgage defaults, combined with agency problems—which map into information and liquidity frictions—can account for macro-level dynamics in the U.S. mortgage finance system.

Additionally, our analysis offers insights into the rationale behind credit guarantees as a tool to stabilize liquidity in the mortgage market. Our evaluation of post-GFC policies highlights deficiencies in the pricing of credit guarantees and emphasizes the need to account for aggregate frictions in securitization when setting guarantee fees. Improving the pricing of guarantees helps reduce borrower credit risk, the probability of market collapses, and government deficits.

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Supplementary Data. Appendix to Mortgage Securitization and Information Frictions in General Equilibrium

A Borrowing cost and House Prices during Credit Expansions

This section presents a comparative static exercise to illustrate how credit supply expansions, driven by increased securitization, result in reduced borrowing costs, higher mortgage debt, and increased house price growth. This exercise is based on the quantitative model outlined in Section 3.

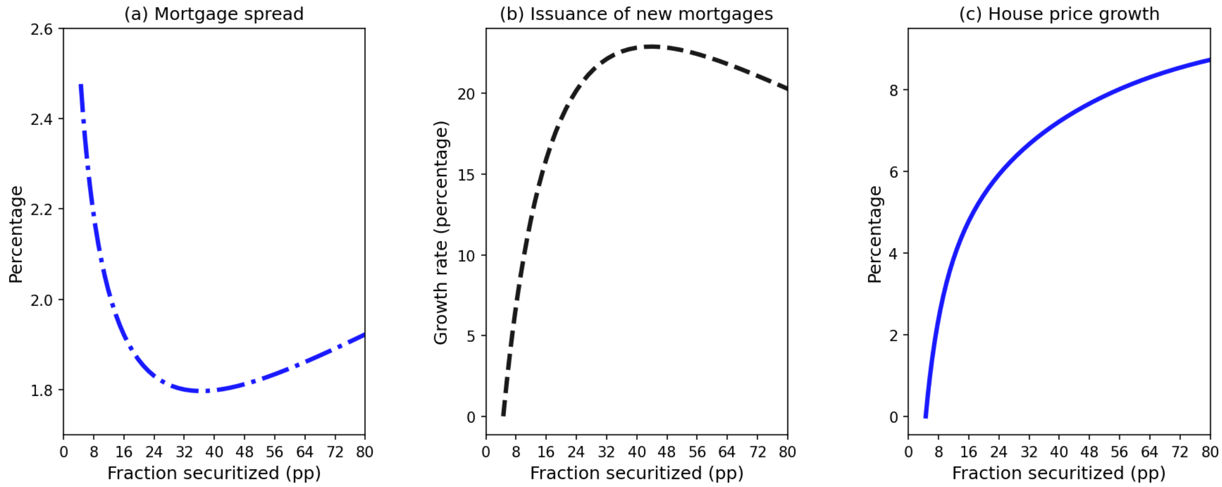
We exploit the steady-state equivalence between our baseline economy and an alternative complete information economy subject to a distortionary wedge, φ. Appendix F presents the recursive representation of a lender's problem (27) in this alternative framework. Our approach involves comparing credit and housing market outcomes across a range of economies (k) with varying levels of securitization.[38] This is achieved by simulating the model for a sequence of distortionary wedge values: $\{\varphi_k\}_{k_0}^{k_{100}}$. For each economy k, we compute all allocations for lenders and the borrower household, and all aggregate outcomes in the economy. Since the volume of securitization issuance is directly tied to the level of the distortionary wedge, we index each economy by the average securitized fraction of lenders' loan portfolios, a statistic representing the prevalence of securitization. An economy with a securitized fraction close to 0 results from setting a high distortionary wedge; such an economy operates as having a credit market without access to securitization. Conversely, a securitized fraction close to 1 implies that the distortionary wedge is low enough to allow lenders to achieve high levels of securitization.

Figure 8 shows how gradually opening the securitization market leads to lower borrowing costs (panel a), higher mortgage debt level (panel b), and higher house price growth (panel c)— growth is computed as the percentage change of the house price level with respect to the economy without access to the securitization market, i.e., where the fraction of securitized loans is zero. As the securitization market opens, it affects the supply side of the credit market through two channels: first, there are efficient gains from having only the lower-cost lenders intermediating credit to borrowers. Second, there is an inflow of liquid funds into the credit market as (lenders) originators can now convert their previously illiquid portfolios into liquid funds. In equilibrium, both effects reduce the average cost of borrowing and increase credit availability to borrowers. Given that borrowers are credit-constrained, they respond to the relaxed credit conditions by increasing their borrowing, which in turn leads to higher housing consumption.[39]

[38] All economies share the same baseline calibration and bear the same level of risk in the deterministic steady state. We set the exogenous process for income and housing volatility to their unconditional mean.

[39] Our model cannot capture the dynamics of homeownership, as it assumes a representative family structure for borrowers (with members perfectly insured against idiosyncratic risk and holding equal housing). However, it predicts aggregate housing consumption dynamics positively correlated with credit availability, aligning with the observed trends in U.S. homeownership, which expanded during the credit boom of the 2000s and contracted following the

Figure 8: Impact of securitization on borrowing costs and house prices



Notes: The panels show the steady-state values of mortgage spreads, the growth of new mortgage debt issuance, and house price growth, respectively, for a given fraction of loans securitized (x-axis).

Our simulation shows that house prices are about 7% higher in an economy with a fully operative securitization market (where more than 60% of mortgage loans are securitized) compared to an economy without securitization, see Panel (c) of Figure 8. Borrowing costs and house price movements are directly linked through the effects of the borrower's binding collateral constraint. In Appendix G.4, we derive the asset pricing versions of the discounted price of credit (32) and the price of housing (34) from the borrower's optimality conditions; combining the steady-state version of both equations through the Lagrange multiplier of the collateral constraint leads to a pricing equation relating both credit and house prices:

$$p^H = \frac{\Lambda R^H}{1 - \Lambda - \pi q(1 - (1 - \phi)\Lambda - \Lambda m)}. \tag{26}$$

This relation highlights how forces driving down mortgage spreads (higher q— discounted price of credit), like the expansion of the securitization market, correspond with increases in house prices.

Although our analysis does not address the dynamics of the 2000s housing boom, our exercise highlights the role of supply-side frictions in credit funding (Justiniano et al. (2019)). As these supply frictions are relaxed, for instance, by technological developments leading to the rapid adoption of securitization, liquidity flows into the mortgage market.[40] This increased liquidity makes credit more accessible to credit-constrained households, a key driving force of house price growth during the housing boom episode (Mian and Sufi (2009)).

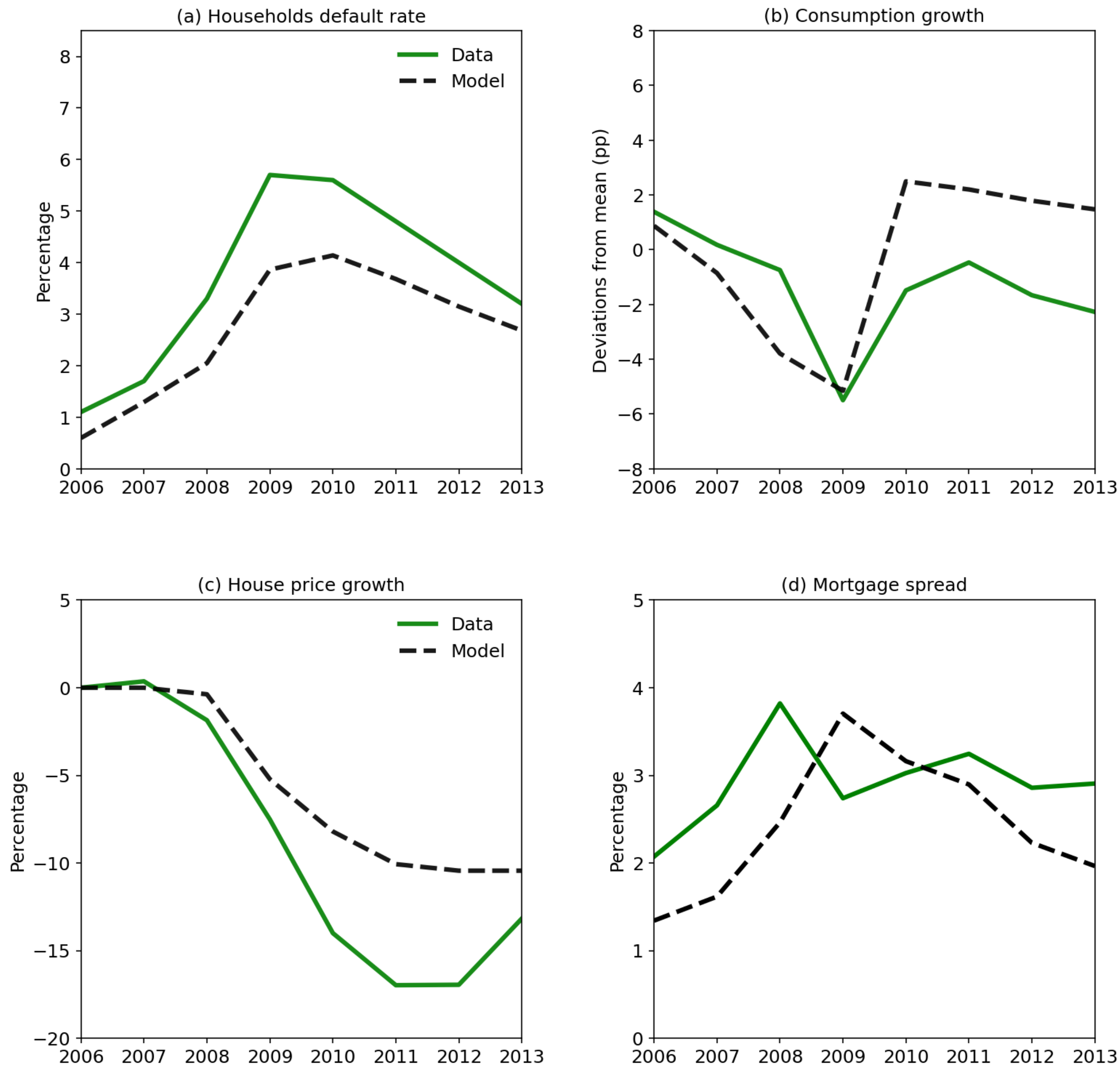
GFC (Favilukis et al., 2017).

[40] Our interpretation is that gradually relaxing structural credit supply frictions allows for expanding and adopting securitization as the main funding source for mortgage lending. Such structural frictions might be linked not only to information frictions but to a wider set of frictions, like regulatory and technological constraints, that initially kept securitization out of the scope.

B Simulations of the Baseline Economy

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

Figure 9: Household aggregates during the Global Financial Crisis



Notes: Panel a. *Data* corresponds to the 90 days or more, or in foreclosure, delinquency 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.

C Proofs and Derivations for the Stylized Model

C.1 Lending with Securitization and Complete Information

Lenders maximize consumption by solving the linear problem: $\max_{\{n,d,s\}} c_1$ s.t $z^j n^j q + pd^j = w + ps^j$. 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 6 summarizes lending and trading decisions for lenders:

Table 6: 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 $D(p,q) = \int_{\frac{p}{q}}^{\bar{z}} d\ \mathrm{d}F(z) = \left(1 - F\left(\frac{p}{q}\right)\right)\frac{w}{p}$.

C.2 Lending with Securitization and Information Frictions

Because of private information among lenders, they 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 7 summarizes lending and trading decisions for lenders in an economy with private information:

Table 7: 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

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

C.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 $(1-\lambda)b_0 F(z^*) = (1-F(z^*))\frac{w}{p^*}$.

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 $g(z) = \frac{1}{z}$.

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

D Calibration Appendix

D.1 Time Series and Cross-sectional Statistics

Table 8: Mortgage credit and securitization volumes in the U.S.

Mortgage market	Pre-GFC 90-06	Post-GFC 13-18	All 90-18
Loans sold or securitized (%)	63.5	71.4	67.3
Securitization by large originators (%)	66.1	74.2	69.9
Securitization by mortgage companies (%)	83.7	94.8	87.3
Correlation (sales, lending)	0.92	0.96	0.94
GSEs market share of MBS issuance	0.69	0.93	0.80

Notes: 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. Source: Loan Application Registries (LAR) and Reporter Panel from the Home Mortgage Disclosure Act (HMDA) dataset, years 1990 to 2018. Data on residential MBS issuance market share, available from 1996 onward, is sourced from SIFMA.

Table 9 summarizes average moments of the cross-sectional distribution of originators by loan volume. Results are similar when restricting to home purchase, conventional, one-to-four family, owner-occupied loans. On average, the top 1% of originators accounted for 64% and the top 10% for 90% of total mortgage lending.[41] A comparable concentration is observed in funding sources, 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, where they play a key role in shaping equilibrium outcomes and the amplification effect of information frictions (Section 5).

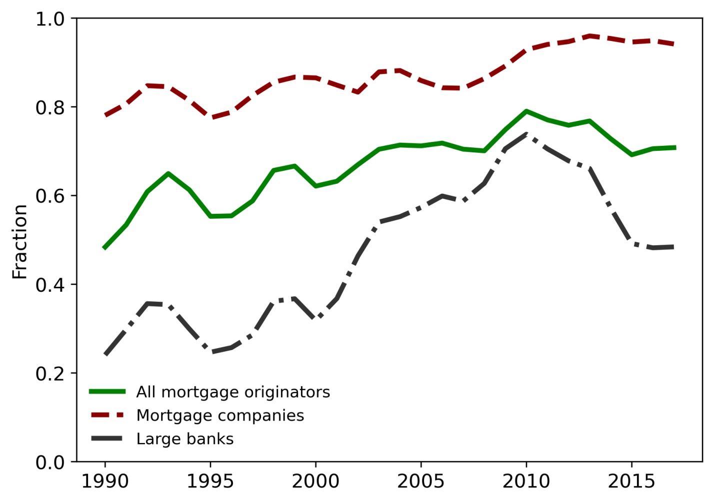
[41] This pattern holds across different types of institutions (e.g., banks, thrifts, mortgage companies) and aligns with findings by Corbae and D'Erasmo (2020), McCord and Prescott (2014), and Janicki and Prescott (2006) on trends in the banking industry.

Table 9: Moments of the distribution of mortgage lending

Concentration measure	1990–2018
Market share top 1%	0.633
Market share top 10%	0.895
Market share top 25%	0.960
Market share top 40 orig.	0.530
Market share Q1 (bottom 25%)	0.002
Market share Q2 (25-50%)	0.008
Market share Q3 (50-75%)	0.029
Market share Q4 (top 25%)	0.960
Lending top 10% / bottom 90%	9.19
Lending top 1% / bottom 99%	1.89
Mean / Median orig. volume	18.64

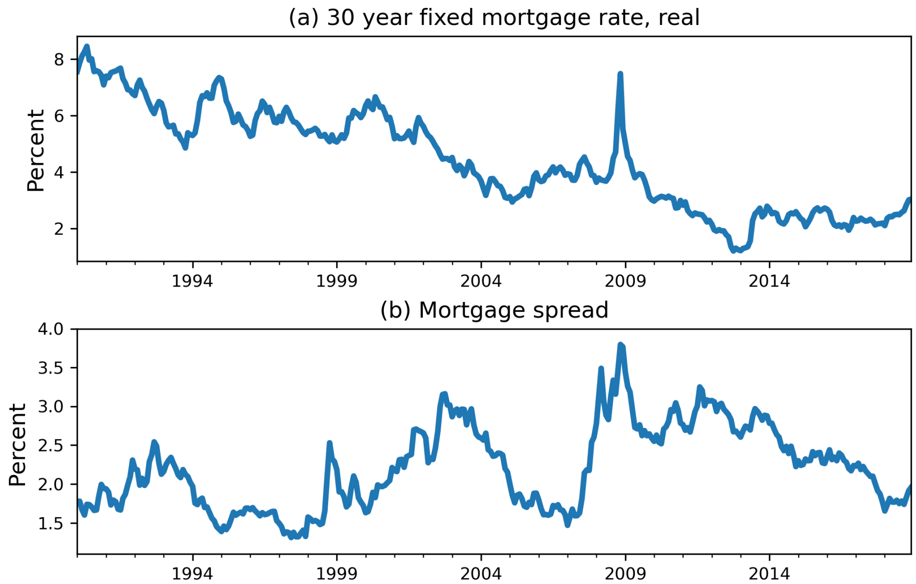
Notes: Average cross-sectional moments for new residential mortgage credit originated in a given year by each reporter in HMDA. 'Top X%' refers to the top X% of institutions by count in the cross-sectional distribution of origination volume (USD). Market shares are expressed as fractions of total annual originations.Source: Loan Application Registries (LAR) and Reporter Panel from the Home Mortgage Disclosure Act (HMDA) dataset, years 1990 to 2018.

Figure 10: Fraction securitized



Source: HMDA Loan Application Registries (LARs) and Reporter Panel, 1990–2018. The fraction of sold or securitized mortgages is the cross-sectional average of the nominal value of mortgages sold or securitized, divided by the nominal value 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 11: Historic mortgage interest rates



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

Table 10: Historic average mortgage rates

Description	90-06	13-18	90-18
Mortgage rate, mean	5.21	2.22	4.10
Mortgage rate, std	1.09	0.35	1.62
Mortgage spread, mean	1.60	1.68	1.66
Mortgage spread, std	0.28	0.10	0.28

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

D.2 Housing Returns and Housing Premia

Tables 11 and 12 compare data vs model generated moments for housing returns, housing premia, and rent growth. In the model, housing returns are defined as: $R^H_t + 1 \equiv \frac{p^H_{t+1}\mu_\omega(\bar{\omega}_t)+Rent^H_{t+1}}{p^H_t}$, where the term $\mu_\omega(\bar{\omega}_t) = \mathbb{E}[\omega^i_t|\omega^i_t \geq \bar{\omega}]$ is the value of housing holdings (among household members who avoid default) net of valuation shocks, which is similar to housing depreciation. In the data, housing returns are $R^H_{t+1} = \frac{p^H_{t+1}}{p^H_t} + \frac{Rent^H_{t+1}}{p^H_t} * 0.055$. We correct the level of the initial rent-to-price ratio in 1976-Q1 to match Campbell et al. (2009)'s rent-to-price of 5.5% at the U.S. national level (as reported in their Table 1). This facilitates comparison across statistics in the Tables below.

Table 11: Returns to housing

	Mean	Std	Corr w/ Rent growth	Corr w/ r^f risk-free
Model	9.20	1.89	0.37	-0.34
Data, 1990-2006	9.42	2.46	0.18	-0.37
Data, other periods				
1990-2019	7.72	4.05	0.41	0.19
1975-2007 (Campbell et al., 2009)	6.47	2.48	> 0	< 0

Notes: For house prices we use the All-transaction House Price Index for the United States, base year 1980. For housing rents, we use the Consumer Price Index for All Urban Consumers: Rent to Primary Residence in U.S. City Average. Housing returns are corrected to match the level of the initial rent-to-price ratio in 1975 in Campbell et al. (2009) at the national level. Source: FRED. Rent growth is computed as the growth rate of housing rents. All growth rates and returns are computed on an annual basis. The 1975-2007 row reports values directly from Table 2 in Campbell et al. (2009).

Table 12 presents the moments for Housing premia Π_t^H, computed as the difference between the return to housing and the risk-free rate: $\Pi_t^H = R_t^H - R_t^f$. As before, the model produces second moments and correlations for housing premia that align with their empirical counterparts. The lower average housing premia reported by Campbell et al. (2009) is due to their use of the real expected yield on a 10-year U.S. Treasury bond as the benchmark risk-free rate, rather than the 1-year Treasury bill.

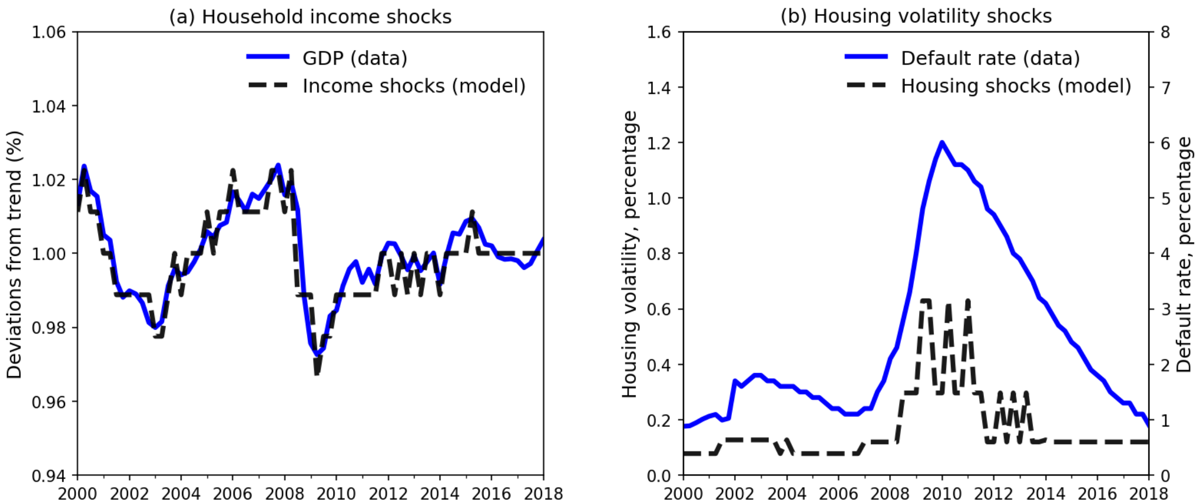
Table 12: Housing premia

	Mean	Std	Corr w/ Rent Growth	Corr w/ Risk-Free
Model	7.50	2.85	0.45	-0.78
Data, 1990-2006	7.67	3.11	0.03	-0.68
Data, other periods				
1990-2019	6.89	4.07	0.29	-0.21
1975-2007 (Campbell et al., 2009)	2.99	3.13	> 0	< 0

Notes: Housing premia is computed as the difference between the return to housing and the risk-free rate. Source: FRED. In the model, the risk-free rate is given by the lenders' stochastic discount factor $R_t^f = \beta \mathbb{E}[U^L_{C_{t+1}}/U^L_{C_t}]$. In the data, we use the 1-year real interest rate. All growth rates and returns are computed on an annual basis. The 1975-2007 row reports values directly from Table 2 in Campbell et al. (2009), who use the real expected yield on a 10-year U.S. Treasury bond as the benchmark risk-free rate.

D.3 Households Income and Housing Valuation shocks

Figure 12: Income and housing volatility shock processes



Notes: 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.4 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 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

Following 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 default 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 50 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:[42]

$\sigma^2_{\omega_{L,1}}$	$\sigma^2_{\omega_{L,2}}$	$\sigma^2_{\omega_{L,3}}$
0.00012	0.00078	0.00120

with transition probability matrix

$$\begin{bmatrix} 0.294 & 0.497 & 0.209 \\ 0.248 & 0.504 & 0.248 \\ 0.209 & 0.497 & 0.294 \end{bmatrix}$$

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

[42]The limited number of observations in the low-volatility regime produces an ill-behaved estimate for the lowest state of $\sigma^2_{\omega_{L,1}}$. We replace it with the bootstrap estimate (0.00012) and verify that the simulated moments match their empirical counterparts.

metropolitan areas are recognized for their significant fluctuations in house prices. To overcome this, we calibrate the two highest states $\{\sigma^2_{\omega_{L,3}}, \sigma^2_{\omega_{H,3}}\}$ in each regime, 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:

$\sigma^2_{\omega_{H,1}}$	$\sigma^2_{\omega_{H,2}}$	$\sigma^2_{\omega_{H,3}}$
0.00127	0.00296	0.00629

with transition probability matrix

$$\begin{bmatrix} 0.397 & 0.466 & 0.137 \\ 0.233 & 0.534 & 0.233 \\ 0.137 & 0.466 & 0.397 \end{bmatrix}$$

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 13 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 13: Fitted moments for income and housing volatility processes

	Income, Y	Volatility, σ^2_ω
mean	1.0001	0.0016
std	0.0137	0.0017
persistence (ρ)	0.8529	0.5085
$\mathbb{E}[X\|\text{crisis}]$	0.9847	0.0034
$\mathbb{E}[X\|\text{normal}]$	1.0080	0.0007
corr(Y, σ^2_ω)	-0.6334	

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.[43] Our specification, although reduced form, captures a

[43] 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.

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 Mortgage Prepayment Rate Projections* 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 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.5 Data Sources

Home Mortgage Disclosure Act - HMDA

This section details the data set and variable construction used in the model's calibration, Section 4. 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. residential lending (Neil et al., 2017).

I construct a panel of mortgage originators for 1990–2018. Using LARs, 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 LARs 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.

Table 14: Description of HMDA LARs 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/

Other Time Series

MBS Issuance. Residential MBS issuance volumes are sourced from SIFMA, see https://www.sifma.org/resources/. Agency residential MBS issuance volumes are obtained by adding up the dollar amount issued by Freddie Mac, Fannie Mae and Ginnie Mae. The volume of residential MBS issuance by non-agency corresponds to private institutions other than the GSEs.

Household Income, measured as the HP-filtered 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 Computational Algorithm

E.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 globally in a discrete state space for endogenous and exogenous state variables. Exogenous states are characterized by the 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 $\mathcal{X} \equiv \mathcal{L} \times \mathcal{Y} \times \mathcal{B} \times \mathcal{H}$. 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 $X \in \mathcal{X}$.

In our baseline calibration, borrowing constraints are always binding. This allow us to reduce the state space to $\tilde{\mathcal{X}} \equiv \mathcal{L} \times \mathcal{Y} \times \mathcal{B}$. In the computational codes, we use a squared grid of 36 points for $\mathcal{B}$, and 21 points for the joint state space (σ_ω, Y). 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 vector of prices that satisfy market clearing conditions for each state in the space of aggregate states.

$$N(q; X) = N^S(p, q; X)$$
$$D(X) = S(X)$$

E.2 Welfare evaluation

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

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

Noting that $\mathbb{E}_{t|t_0} V(\tilde{c}_t, \tilde{h}_t; S_t) \equiv \sum_{t=0}^{\infty} \beta^t \left((1-\theta) \log((1-\tilde{\alpha})\tilde{c}_t) + \theta \log \tilde{h}_t \right)$ and solving for $\tilde{\alpha}$ obtains:

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

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

F Quantifying Information Frictions

In this section, we construct a comparable complete information economy that incorporates similar distortions and government policies as the baseline economy with private information. This alternative setup serves as a reference to evaluate the role of information frictions in amplifying the effects of income and housing shocks. Why is this necessary? As shown in Section 2, a complete information economy eliminates adverse selection in the securitization market, and the need to implement government policies (such as credit guarantees and origination fees) aimed at improving liquidity. Such an economy is not a suitable counterpart for studying the amplification effects of information frictions, since it bears no concept of distortions in lenders' decisions. To build a comparable economy, we adopt the approach of Chari et al. (2007), which measures and maps economic frictions into wedges that distort agents' optimal decisions. This method aligns with Kurlat (2013), who demonstrates how information frictions can be represented as a tax on secondary market transactions in a canonical model of asset creation and reallocation.

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. 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:

$$\begin{aligned}
V(b,z;X) &= \max_{\{c,n,b',d,s_h,s_\ell\}} \left[u(c) + \beta^L \mathbb{E}_{X'} V(b',z',X')|X\right] \qquad (27)\\
s.t. & \\
c + n(zq+\gamma) + pd(1-\tau)\varphi &\leq ((1-x_\ell)b - s_h)\, m_h + x_\ell b m_\ell + p s_h + d_t m_d \varphi - T^L b + T^{\varphi} b \\
b' &= (1-\phi)\left((1-x_\ell)b - s_h + x_\ell b(1-\rho) + d\right) + n \\
& n \geq 0 \quad d \geq 0 \\
& s_h \in [0, (1-x_\ell)b]
\end{aligned}$$

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 (27) can be characterized following the same strategy presented in Appendix G. Similar to the private information economy, 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 the private information economy. The recursive problem of a lender in a complete information economy facing a distortionary wedge is equivalent to the problem a lender faces in the private information economy presented in (17) for an appropriately chosen sequence $\{\varphi_t\}_{t=0}^{\infty}$. Start by conjecturing that prices $\{p_t, q_t\}$ coincide in both economies. Since government policy is kept fixed in both, it must be that the first cut-off $z_t^S \equiv \frac{1}{q_t}\frac{p_t-m_{ht}}{(1-\phi_t)} - \frac{\gamma_t}{q_t} \equiv \tilde{z}_t^S$ is the same. Furthermore, whenever the information-wedge $\varphi_t = \frac{1}{1-\mu_t^*}$ where μ_t^* is the equilibrium value of the private information economy, the second equilibrium cut-off of both economies also coincides and, the level of distortions faced by lenders in the securitization market is the same.

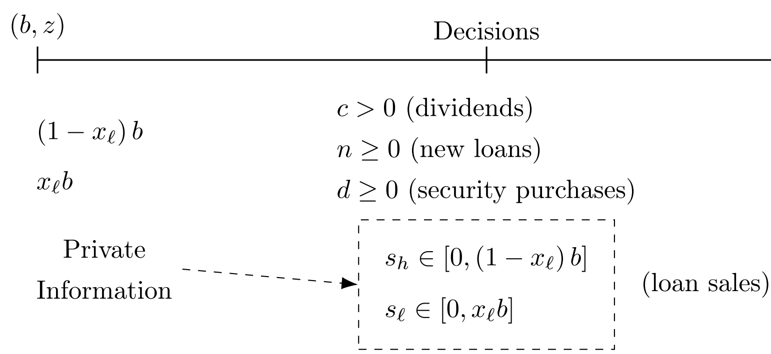
Shock decomposition with information frictions. The main idea of our decomposition is to isolate the impact of information frictions in the transmission of shocks by performing a comparative analysis between the economy with an endogenous wedge—arising from information frictions—and the alternative economy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

First, we simulate the baseline 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. It is important to note that the comparable complete information economy shares the exact calibration as the baseline economy with information frictions. Then, we simulate both economies for the identical sequences of income and housing volatility shocks presented in Figure 12 in the Appendix D. The dynamic responses of aggregate credit and securitization volumes from each economy compared to their data counterparts are shown in the main text; see Figure 6 in the main text.

G Additional Derivations for the Quantitative Model

G.1 Timeline for lenders decisions

Figure 13: Timeline for lenders' decisions



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.

G.2 Additional derivations for the lender's problem

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.

$$V(b,z,X) = \max_{\{c,n,b',d,s_h,s_\ell\}} \left[u(c) + \beta^L \mathbb{E}_{X'|X} V(b',z',X')|X\right]$$

$$s.t.$$

$$\begin{aligned} c + zqb' + \gamma b' = &(zq+\gamma)(1-x_\ell + x_\ell(1-\rho))(1-\phi)b + ((1-x_\ell)m_h + x_\ell m_\ell)b - T^L b \\ &+ s_h\left(p - m_h - (zq+\gamma)(1-\phi)\right) \\ &+ s_\ell\left(p - m_\ell - (zq+\gamma)(1-\phi)(1-\rho)\right) \\ &+ d\left((zq+\gamma)(1-\phi)(1-\mu) + m_d - p(1-\tau)\right) \end{aligned}$$

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 $\{z^S, z^B\}$.[44] 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 $n = 0$.

[44] 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.

- 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.

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:

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

G.3 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 cumulative distribution function 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 $\{N, H', \bar{\omega}\}$:

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

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

$$
q = \tilde{\xi} + \beta^B \mathbb{E}\left[\frac{U_c'}{U_c}(1-\lambda(\bar{\omega}'))(q'(1-\phi')+m')\right] \tag{28}
$$

$$
p^H(1+\Xi_{H'}-\pi\tilde{\xi}) = \beta^B \mathbb{E}\left[\frac{U_c'}{U_c}\left((1-\lambda(\bar{\omega}'))\mu_\omega(\bar{\omega}')p^{H'} + \frac{U_H'}{U_C'}\right)\right] \tag{29}
$$

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:

$$
\begin{aligned}
U_c(-\bar{\omega}g_\omega(\bar{\omega})p^H H + g_\omega(\bar{\omega})mB) + \tilde{\xi}(1-\phi)g_\omega(\bar{\omega})B &= -\beta^B \mathbb{E}\left[\frac{\partial V}{\partial B'}\frac{\partial B'}{\partial \bar{\omega}}\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega}p^H H + mB) + U_c\tilde{\xi}(1-\phi)g_\omega(\bar{\omega})B &= \beta^B \mathbb{E}\left[\frac{\partial V}{\partial B'}(1-\phi)g_\omega(\bar{\omega})B\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega}p^H H + mB + \tilde{\xi}(1-\phi)B) &= (1-\phi)g_\omega(\bar{\omega})B\left[\beta^B \mathbb{E}[V_{B'}]\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega}p^H H + mB + \tilde{\xi}(1-\phi)B) &= -(1-\phi)g_\omega(\bar{\omega}_h)BU_c(q-\tilde{\xi}) \\
\bar{\omega} &= \frac{B}{p^H H}[m+(1-\phi)q]
\end{aligned} \tag{30}
$$

G.4 The Prices of Credit and Housing

From the borrowers' FOCs conditions for mortgage debt (28) and housing (29), we can derive the equilibrium pricing equation for the discounted price of credit and house prices:

$$
\begin{aligned}
q &= \tilde{\xi} + \mathbb{E}\left[\Lambda(q'(1-\phi')+m')\right], \\
p^H &= \frac{1}{1+\Xi_{H'}-\pi\tilde{\xi}}\ \mathbb{E}\left[\Lambda(p^{H'}+R^{H'})\right],
\end{aligned}
$$

where $\Lambda \equiv \beta^B \frac{U_c'}{U_c}(1-\lambda(\bar{\omega}'))\mu_\omega(\bar{\omega}')$ represents borrowers' discount factor after considering defaults and housing valuation shocks. In the house pricing equation, we denote the marginal rate of substitution between housing and non-housing consumption by $R^{H'} \equiv \frac{U_H'/U_C'}{(1-\lambda(\bar{\omega}'))\mu_\omega(\bar{\omega}')}$, which represents the value of housing rents services to the borrower household.

Switching from a recursive to a discrete time representation and iterating forward each equation, we obtain the asset pricing representation for both equilibrium prices. The discounted price of mortgage credit can be expressed as the sum of future mortgage payments:

$$q_t = \tilde{\xi}_t + \mathbb{E}_t \left[\Lambda_t(q_{t+1}(1-\phi_{t+1}) + m_{t+1})\right], \tag{31}$$

$$= \mathbb{E}_t \left[\sum_{\tau}^{\infty} \Lambda_{t,t+\tau}\tilde{\xi}_{t+1+\tau} + \sum_{\tau=1}^{\infty} \Lambda_{t,t+\tau-1} m_{t+\tau}\right], \tag{32}$$

where in the second equation, without loss of generality, we have assumed $\phi_t \approx 0 \ \forall t$ (which implies that mortgage loans mature in one period). In a similar fashion, house prices at t as a function of the sum future expected housing rents (housing dividend services):

$$p_t^H = \frac{1}{1 + \Xi_{H_{t+1}} - \pi\tilde{\xi}_t} \ \mathbb{E}_t \left[\Lambda_t(p_{t+1}^H + R_{t+1}^H)\right], \tag{33}$$

$$= \mathbb{E}_t \left[\sum_{\tau}^{\infty} \frac{\Lambda_{t,t+\tau} R_{t+1+\tau}^H}{\Pi_{k=0}^{\tau}(1 + \Xi_{H_{t+1+k}} - \pi\tilde{\xi}_{t+k})}\right] \tag{34}$$

In our setup the collateral constraint for household binds in equilibrium, implying that the associated Lagrange multiplier is always positive in all periods $\tilde{\xi}_t > 0$ in all periods. This feature establishes a direct link between the dynamics of credit pricing and house price movements. Specifically, shocks that lead to a increase in the discounted price of credit (i.e., lower mortgage rates) correspond with increases in house prices. This relationship becomes evident when considering the steady-state version of the pricing equations (31): $q = \frac{\tilde{\xi}+\Lambda m}{1-(1-\phi)\Lambda}$ and (33): $p^H = \frac{\Lambda R^H}{1-\pi\tilde{\xi}-\Lambda}$. Combining both expressions through the Lagrange multiplier of the collateral constraint leads to a pricing equation relating both credit and house prices:

$$p^H = \frac{\Lambda R^H}{1 - \Lambda - \pi q(1-(1-\phi)\Lambda - \Lambda m)}.$$